Subjective self-assessment and decision making under uncertainty

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Chapter 1

Introduction

Decision making under uncertainty relies on subjective assessments of probabilities and outcomes of possible states of the world. How individuals form these assessments has been subject to a controversial dispute among economists. A popular hypothesis is that individuals use all relevant information when forming their assessments or expectations and learn from past errors. According to this rational expectations hypothesis expectations may turn out to be individually wrong, but are correct on average. Thus, expectations are assumed to equal their true statistical expected value which rules out the possibility of systematic expectation errors (see the seminal paper on rational expectations by MUTH, 1961).

The rational expectation hypothesis is part of the overall concept of the Homo Economicus which has provided the basic behavioral assumption in many standard economic theories. The unemotional and self-interested Homo Economicus acts rationally to obtain the highest possible well-being given his preferences and information about his opportunities. Homo Economicus is rational in the sense that, based on his unbiased judgments, he follows the economic principle of choosing actions in order to attain his subjectively defined goals to the greatest possible extent given his available resources. One implication of the standard economic approach is that, at least on average, individuals are able to identify and choose what is best for them. In the context of decision making under uncertainty, Homo Economicus always acts in accordance with several rationality requirements, like the independence axiom of expected utility theory or consistency with first-order stochastic dominance (see e.g. MILL, 1836, KIRCHGÄSSNER, 1991, and PERSKY, 1995, for characteristics and the origin of Homo Economicus).

In contrast, behavioral economics acknowledges that in reality humans sometimes systematically fail to identify the optimum or to choose what they have identified as the optimum. Behavioral economics integrates insights from psychology and sociology into economic thinking and tries to formalize ways in which behavior differs from the predictions of standard theories. Essentially, three bounds of human nature in judgment and choice have so far been established: bounded rationality, bounded willpower and bounded self-interest. Bounded rationality refers to the fact that human information processing or cognitive abilities are limited which, in contrast to the rational approach, allows for systematic errors in expectation formation. Bounded willpower or incomplete self-control means that people sometimes act in conflict with their own long-term interest. Finally, bounded self-interest captures the fact that preferences may have a social dimension which leads people to sacrifice their own interests for the benefit of others (see e.g. Mullainathan and Thaler, 2000, Camerer et al., 2003, Diamond and Vartiainen, 2007, or DellaVigna, 2009, for overviews of the behavioral economics approach).

Given this general background, this thesis deals with standard and behavioral perspectives on the role of expectations in individual decision making. Chapter 2 considers the influence of subjective expectations on insurance demand. The analysis takes a standard approach by arguing that the subjective risk assessment of the insurant contains elements of private information which makes it superior to the objective risk assessment made by the insurer. Exploiting private information in decision making is fully consistent with the rationality criterion. In contrast, Chapters 3, 4 and 5 take a behavioral approach to decisions under uncertainty and subjective assessments. Chapter 3 experimentally investigates whether risk preferences deviate from the assumptions of expected utility theory and the basic rationality requirement of consistency with first-order stochastic dominance. Chapters 4 and 5 consider the behavioral implications of deviations of subjective from objective assessments which are caused by a systematic bias instead of a private information advantage. Contradicting the rationality postulate and ruled out within the standard framework, the occurrence of systematic errors in subjective belief formation prevents individuals from efficient decision-making.

More precisely, Chapter 2 empirically examines determinants of the individual decision to take up a private pension insurance policy. Standard economic theory offers a strong theoretical foundation for welfare-enhancement of annuities. Conflicting with this theoretical prediction, the actual take up of annuities is remarkably low. This phenomenon is known as the annuity puzzle. There are several competing explanations for the annuity puzzle within a standard framework. Most prominent is the hypothesis that the annuity market is characterized by adverse selection which implies prohibitively high insurance premiums for low-risk individuals. Selection into insurance schemes may take place either actively or passively. Here, active selection refers to the use of private information about expected longevity when deciding about the insurance purchase. Passive selection means that annuitants tend to have higher income and wealth than non-annuitants, factors which are also correlated with mortality. Active and passive risk selection may contribute to mortality rates of annuitants which are substantially below that of the general population and thus result in relatively high insurance premia. Possibly, the inability of insurance companies to hedge aggregate mortality risk in the population adds to the price mark-up (see e.g. Blake et al., 2002, Brown and Orszag, 2006). Alternative rational explanations for limited annuity demand include pre-existing annuitization, risk-sharing in couples or the existence of bequest motives (Brown, 2007).

The analysis in Chapter 2 contributes to an assessment of the validity of adverse selection as a rational explanation for the annuity puzzle. For that purpose, the determinants of private pension insurance uptake of German households are empirically investigated. While the analysis takes into account some insights from behavioral economics, a special emphasis is put on the role of subjective life expectancy for the decision to take up pension insurance. In fact, subjective life expectancy is found to be positively related with the probability of having supplementary private pension insurance. Consistent with standard theories of insurance demand, the analysis thus provides micro level evidence for active risk selection into insurance schemes. The empirical result suggests that the German private pension insurance market is actually characterized by adverse selection. However, as will be shown later, the effect is quantitatively small which calls for additional (behavioral) explanations of the present phenomenon.

Chapter 3 studies choice under risk of small-holder farmers in a developing country. In monetarily incentivized experiments, consistency of choices under risk with the predictions of expected utility theory and the criterion of first-order stochastic dominance is tested. Expected utility theory is the dominant theory of decision making under risk in economics. It defines rational decision making based on a set of axioms -completeness, transitivity, continuity and independence- which thus provide criteria for testing rationality of choice. Most controversial is the independence axiom, while the axioms of completeness, transitivity and continuity are rather uniformely accepted. The independence axiom states that for any three lotteries p, q and r, $p \succ q$ implies $\lambda p + (1-\lambda)r \succ \lambda p + (1-\lambda)r$ for all λ from the interval $(0, 1)$, where $p \succ q$ means that p is preferred to q. Consistency of choices with the independence axiom is tested by offering two pairs of lotteries where the second set of lotteries is derived from the first as stated in the axiom. This experimental design is known as the common ratio problem and has been introduced by Allais, 1953. First-order stochastic dominance is a rational principle of decision making that posits that stochastically dominating gambles are preferred over stochastically dominated gambles. A gamble A first-order stochastically dominates a gamble B if for any monetary outcome x, A gives an at least as high probability of receiving at least x as B does, and for some x, A gives a higher probability of receiving at least x. Consistency with the criterion of first-order stochastic dominance is tested by offering a pair of lotteries where one lottery first-order stochastically dominates the other. The results suggest that systematic violations of the independence axiom and stochastic dominance occur not only in samples from the developed world, but also from the developing world. An analysis of the determinants of violating the independence axiom and stochastic dominance using complementary survey data indicates that psychogical traits of the decision maker tend to be more relevant than sociodemographic characteristics.

Chapters 4 and 5 of the thesis then proceed with a behavioral analysis of the role of systematic errors in beliefs for individual decision making. The type of bias under consideration is overconfidence as according to DeBondt and Thaler, 1995, "perhaps the most robust finding in the psychology of judgment is that people are overconfident". Overconfidence generally refers to upward biased beliefs of individuals about their abilities and personal attributes and represents one example of bounded rationality (Mullainathan and Thaler, 2000). It has been identified as one of the most important systematic violations of theories of rational belief formation (Hvide, 2002, DellaVigna, 2009). The literature distinguishes three types of overconfidence. The first type of overconfidence is given by unrealistic positive self-evaluations and refers to the tendency of overestimating one's own positive attributes in absolute terms or relative to others (Greenwald, 1980). The second concept of overconfidence is a systematic overestimation of the precision of one's knowledge which implies an underestimation of the variance of random variables. This type of overconfidence is often referred to as miscalibration (Lichtenstein et al., 1982). A third stream of literature regards overconfidence as illusion of control (Langer, 1975) and unrealistic optimism which means that people overestimate personal success probabilities. Numerous studies provide evidence for the presence of overconfidence of all types in different samples.

My dissertation considers the behavioral implications of overconfidence in two different decision situations. First, the impact of unrealistic positive self-evaluations during preparation for a future task on performance and subjective well-being of the decision maker is assessed. Second, the role of unrealistic positive self-evaluations and unrealistic optimism for risk taking in an income generation process are evaluated. Both studies in Chapter 4 and 5 of the thesis provide theoretical and empirical evidence for welfare-reducing effects of overconfidence.

Chapter 4 studies the implications of overconfidence during preparation for a future task. It is argued that overconfidence is associated with twofold costs as it lowers objective performance and subjective well-being. The study shows theoretically and empirically that overly optimistic beliefs about one's own existing knowledge are detrimental for future objective task performance and subjective well-being. A utility-based model is used to demonstrate that the erroneous feeling of mastering a task induces an underestimation of the marginal productivity of subsequent effort. Therefore, overconfidence leads to less than optimal effort spending and inefficiently low performance. The loss of subjective well-being is a consequence of the inefficiently low performance combined with an expectation-inflating effect of overconfidence. The theoretical predictions are confirmed in an empirical application of the model to the learning process of university students who spend study effort to accumulate knowledge.

Chapter 5 examines the impact of overconfidence on risk taking in the income generation process. It is argued that an unrealistic positive view of the own abilities leads to overly high expected returns from pursuing an income generating activity. Consequently, the willingness to take risk associated with an activity raises. In a sample of poor small-holder farmers from Ethiopia, the study empirically shows that farmers who overestimate their ability to generate crop yields cultivate riskier crops. Consequently, overconfident farmers experience larger income fluctuations. Overconfidence causes a welfare loss to the decision-maker and his dependents due to the absence of efficient insurance tools and the dependence on costly informal coping mechanisms in case of income losses. Chapter 6 concludes.

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Chapter 2

Subjective Life Expectancy and Pension Insurance Demand[1]

2.1 Introduction

The German welfare state comprises a public pay-as-you-go (PAYG) pension system designed to prevent old-age poverty and to maintain the standard of living after withdrawal from working life. In contrast to funded systems, a PAYG plan is directly financed from current contributions and therefore requires a nearly permanent balance of contributions and payments. Population aging and negative incentive effects have increasingly threatened the German system and triggered a reform process to keep its financing sustainable. This has been accompanied by a lively discussion of the system's opportunities and limitations, that has created awareness of falling replacement rates from the public statutory system and the need for supplementary private old-age provision. In addition to pure accumulation of financial and non-financial assets, investment in private pension insurance policies presents one possible way to raise retirement income and concomitantly insures against outliving one's wealth. Consequences of shifting substantial parts of old-age provision from the public to the private sector, however, depend on the efficiency of this market.

A main concern over insurance markets raised by theoretical research, is the presence of information asymmetries between insurers and the insured that lead to market failure due to moral hazard and adverse selection. As pension insurance covers the financial risk related to longevity, moral hazard would be present if pension insurance coverage induced life-prolonging behavior that cannot be observed by the insurer. Adverse selection would be present if the length of life could be more accurately predicted by the insurant himself than by the insurer, and people expecting relatively long life

[1]This chapter is a slightly modified version of the article "Betting on a Long Life - the Role of Subjective Life Expectancy in the Demand for Private Pension Insurance of German Households" jointly written with Katharina Schulte and published in the Journal of Applied Social Science Studies (Schmollers Jahrbuch), 132 (2012), 233–263.

systematically purchased larger pension insurance coverage. Concerning moral hazard, most people agree that in developed countries like Germany individual life-prolonging activities can be seen as independent of pension insurance coverage. Moral hazard is therefore reasonably assumed to be quantitatively negligible, if not non-existent.[2] In contrast, adverse selection in pension insurance markets is a concern. As a consequence of adverse selection, premiums rise and eventually become prohibitively high for low-risk individuals who are pushed out of the market.

In an attempt to explain the observed low uptake of annuities -the *annuity puzzle*-related studies consistently provide evidence for adverse selection in the UK and the US annuities market (Finkelstein and Poterba, 2002, 2004, for the UK and Friedman and Warshawsky, 1990, Mitchell et al., 1999, Brown, 2001, and Brown et al., 2008a, for the US). First empirical evidence by Gaudecker and Weber, 2004, suggests that the German private pension market is also characterized by adverse selection. If this was the case, it might be too expensive for individuals who expect to die early to compensate public pension shortfalls by private pension insurance.

Our work contributes to the literature on adverse selection in annuity markets. In contrast to most related studies that take the *Money's Worth* approach introduced by Friedman and Warshawsky, 1988, we investigate the existence of adverse selection on the micro level. Our main interest is the explanatory power of subjective life expectancy in the uptake of private pension insurance. According to previous research, subjective life expectancy is a remarkably good predictor of actual lifetime. In particular, it is superior to predictions based on mortality tables as made by the insurers (Hamermesh, 1985, Hurd and McGarry, 1995, 2002). Expectations about lifetime therefore represent private information and give a risk selection opportunity to the insurants as return on investment of a pension insurance policy increases with lifetime. In the same vein, a study on formation and updating of subjective life expectancy by Steffen, 2009, finds correlations of subjective life expectancy with private information like individual health behavior and health status as well as rational updating of expectations after e. g. adverse health shocks. Based on these findings, our work now seeks to answer the question whether people actually make use of their private information about lifetime when deciding about old-age provision. If, conditional on other relevant determinants, subjective life expectancy was positively associated with the probability of having supplementary private pension insurance, this would indicate adverse selection in this market.

We will test this hypothesis using the German SAVE survey data on savings and old-age provision. Guided by the theory of savings and the life cycle with uncertain time of death beginning with Yaari, 1965, and previous empirical studies, we provide an in-

[2] This view is shared in large parts of the literature; see among others Finkelstein and Poterba, 2004, and Rothschild, 2009. See, however, Philipson and Becker, 1998, for a discussion of the existence of moral hazard effects in the market for annuities.

depth analysis of the determinants of pension insurance uptake of German households with a special focus on the role of subjective life expectancy. The remainder of this paper is organized as follows: Section 2.2 gives an overview of the related theoretical and empirical literature. The German Old-Age Pension System is presented in Section 2.3. Section 2.4 describes the data and methodology in use and contains estimation results. Section 2.5 concludes.

2.2 Related literature

Within an overall assessment of the determinants of pension insurance uptake, we specifically focus on the role of subjective life expectancy to understand whether the German private pension market is characterized by adverse selection. Our work thus mainly relates to two broad strands in the literature. First, we refer to the theoretical and empirical literature on life cycle savings and annuity demand dealing with optimal annuitization in portfolio choice and practically relevant determinants of the annuitization decision. Second, we refer to the theoretical and empirical discussion of adverse selection in insurance markets in general and in annuity markets in particular.

Yaari, 1965, was the first who incorporated uncertain lifetimes in the classical life cycle savings theory of Modigliani and Brumberg, 1954. His model is a theoretical conjunction of mortality expectations and time and risk preference parameters in determining optimal annuitization. The main implication of his theory of consumption under the presence of longevity risk is that risk averse utility maximizing consumers who face actuarially fair insurance prices should fully annuitize their wealth, provided that they do not have any bequest motive. Davidoff et al., 2005, later confirmed the complete annuitization result within a more general framework.

Compared to the theoretical predictions of full or at least high annuitization, observed uptake of annuities is surprisingly low (Friedman and Warshawsky, 1990, Brown and Poterba, 2000, James and Song, 2001, and James and Vittas, 2000). This gap between theory and reality has caused a large body of literature dedicated to resolve this so called *annuity puzzle*. Among potential explanations for the puzzle are adverse selection, administrative load factors, bequest motives, risk-sharing within families, pre-existing annuities from social security, financial illiteracy and precautionary savings for the event of unexpected expenditure shocks. In this context, Brown, 2001, empirically investigates the behavioral relevance of Yaari's life cycle model by relating a utility measure of annuity value to actual household decisions. Following the life cycle model, he calculates the utility measure - the *annuity equivalent wealth* - based on cohort mortality tables and survey data on risk aversion, marital status, and the presence of pre-existing annuity flows from social security. Brown, 2001, finds that households for which the life cycle model predicts to have a higher valuation of annuities are in fact more likely to annuitize their retirement resources. However, in accordance with the annuity puzzle, much of the variation in the actual decision remains unexplained by the life cycle model. He therefore considers several additional factors that might influence the annuitization decision where he identifies individual health status and time horizon for financial decision-making to be the most relevant.

Related to our research purpose, the importance of individual health status in explaining the actual annuitization decision conditional on average mortality from life tables is particularly interesting. It points to the fact that people use private information on health status and expected longevity in the old-age provision decision which would be consistent with the presence of adverse selection in annuity markets. A general theoretical framework of adverse selection was introduced by Akerlof, 1970, which Rothschild and Stiglitz, 1976, later applied to the insurance market. The basic idea is that private information about individual risk gives insurants an information advantage over the insurer which allows higher-risk individuals to self-select into insurance contracts. Pooled risks are then comparatively high, insurance premiums rise and crowd lower-risk individuals out of the market. Thus, the theory of adverse selection predicts a positive correlation between insurance coverage and risk.

A wide body of literature studies the empirical importance of adverse selection in insurance markets. Two markets that have been frequently studied are the automobile and the health insurance market. For the automobile insurance market, the early studies of Dahlby, 1983, and Puelz and Snow, 1994, suggest a positive coverage-risk correlation, which, however, was not reinforced by subsequent research (Chiappori and Salanié, 2000, and Dionne et al., 2001). Conflicting findings are also available for the health insurance market. While Cutler and Zeckhauser, 1998, support the theoretical prediction of positive correlation, Cardon and Hendel, 2001, and Fang et al., 2008, reject it. Available studies on the market for life insurance (Cawley and Philipson, 1999, and McCarthy and Mitchell, 2010) so far consistently suggest absence of adverse selection.[3]

Concerning annuity markets, the empirical literature rather uniformly concludes that these are characterized by adverse selection. From a methodological point of view, two different strands of empirical investigations of adverse selection in the market for annuities can be distinguished. Roughly, the first strand compares mortality data of annuitants with mortality data of non-annuitants or the general population, respectively. This strand includes the large number of studies that apply the concept of *Money's Worth* to identify how much of an insurance premium's deviation from the actuarily fair premium can be attributed to selection effects. Friedman and Warshawsky, 1988, introduced the money's worth approach that was later refined by Mitchell et al., 1999. By now, the money's worth is commonly understood as the expected net present value of payouts in relation to premium costs which is calculated separately using population and insurance mortality tables. Several studies applied this concept to investigate the extent of adverse selection in annuity markets in various countries. Most frequently studied are the markets in the US (Friedman and Warshawsky, 1990, and Mitchell et al., 1999) and in the UK (Finkelstein and Poterba, 2002, 2004). Further examinations have been done for Germany (Gaudecker and Weber, 2004), Australia (Doyle et al., 2004) and Singapore (Doyle et al., 2004, and Fong, 2002), as well as for Canada, Chile, Israel and Switzerland (James and Song, 2001).

[3]See Cohen and Siegelman, 2010, for a recent review of the empirical literature on adverse selection in insurance markets.

McCarthy and Mitchell, 2010, and Rothschild, 2009, also compare mortality tables of policyholders with those of the general population, but do not explicitly calculate the money's worth. All these studies find evidence for adverse selection which, however, can only partially explain the annuity puzzle due to its limited extent.

The more recent second strand, where our study belongs to, analyzes adverse selection from the perspective of the policyholder using micro level data. While the focus of the first strand lies on a quantitative estimation of the effects of adverse selection on insurance premiums, the second strand is able to simultaneously assess the relevance of subjective life expectancy and other determinants of annuity uptake. In addition, the money's worth does not allow to distinguish between active mortality selection based on asymmetric information about health and expected longevity and passive mortality selection reflecting other differences such as wealth and income that are also correlated with mortality (Finkelstein and Poterba, 2002). Due to data limitations, research on the micro level is less frequently done. Most closely related to our analysis, is the study by Brown et al., 2008a, who use data from the US Health and Retirement Study (HRS). They investigate self-reported willingness of the elderly population to exchange part of their social security inflation-indexed annuity benefit for an immediate lump-sum payment by self-reported health status and subjective survival probabilities relative to actuarial life tables. Their results are consistent with predictions of standard theoretical models of adverse selection, since individuals with poor health-status and pessimistic life expectations are less likely to annuitize, but tend to prefer lump-sum payments. Another related study by Inkmann et al., 2011, uses the English Longitudinal Study of Aging and investigates actual annuity uptake in the UK. In line with Brown et al., 2008a, they find that the subjective survival probabilities of annuitants are significantly higher than those of their non-policyholding counterparts which points to the presence of adverse selection in the UK's annuity market as well.

Our work differs from the existing studies in several aspects: Compared to the US and the UK, Germany is characterized by a dominant public statutory system which leaves a relatively smaller scope for supplementary private insurance. Consequently, selection effects in the private pension insurance market in Germany are likely to differ from those observed in the US and the UK. In contrast to Brown et al., 2008a, who consider stated intentions to annuitize retirement income, we are able to observe actual demand for private pension insurance of households. Compared to Inkmann et al., 2011, we dispose of a more comprehensive set of variables, as we are able to build proxies for preference parameters reflecting risk aversion and time preference that are not included in their data. Unlike Brown et al., 2008a, and Inkmann et al., 2011, we use subjective life expectancy in years instead of subjective survival probabilities in percent. This overcomes the difficulties respondents might have with thinking in probabilities, especially when it comes to very low or very large probabilities as suggested by prospect theory (Kahneman and Tversky, 1979).

2.3 The German old-age pension system

For our further analysis, it is instructive to briefly examine the German old-age pension system which consists of three coexisting pillars. Three things should be noted from the following description. First, the public first pillar is still by far the most important source of old-age income. Second, benefit levels from the first pillar differ for different population groups mainly depending on their type of employment. Third, the private pension insurance considered in our work is part of the third pillar and allows anyone to supplement pre-existing benefits.

Introduced by Otto von Bismarck in 1889 as a fully funded system, the German public old-age pension system was gradually converted into a PAYG system from 1957 on. Generosity was a key characteristic of the German system after the 1972 reform in terms of both replacement rates and flexibility of retirement age. However, increasing life expectancy in times of low fertility and the resulting population aging coupled with negative incentive effects as well as the additional financing need after the German reunification began to threaten the system. Starting with a major reform in 1992, benefit cuts were implemented in an effort to stabilize its functioning (Börsch-Supan and Wilke, 2004). Nowadays, the so-called *first pillar* of the three-pillar old-age provision system comprises statutory pension insurance for all employees covered by the German social security system, old-age security for farmers, professional provision for certain groups of self-employed like physicians, lawyers and architects as well as the civil-service pension scheme. Except for the self-employed who are at liberty to participate and some other occupational groups like farmers or soldiers who can apply for exemption from compulsory insurance, the whole work force is subject to mandatory coverage within the first pillar. Although the relative importance of the three pillars has changed in disfavor of the first pillar, it still constitutes the most important source of old-age income. In 2007, the public pension scheme covered about 92% of the German elderly and accounted for about 76% of total gross old-age income of all retirees (Kortmann K. and Halbherr V. 2009).

The various subsystems within the first pillar, like the old-age security for farmers or the civil-service pension scheme have neither historically been equally generous, nor have they undergone benefit cuts in an equal measure. In particular, in 2007, persons of age 65 and older whose last position was denoted as civil-servant, drew an average monthly gross pension of 2670 € from the public system. This amounted to an average of 1195 € for former blue- and white-collar worker and to only 813 € for former farmers and self-employed who were least secured by the public scheme (Kortmann K. and Halbherr V. 2009).

Employees in the private and the public sector are free to supplement their benefits from the mandatory statutory pension insurance by an occupational pension scheme within the capital funded *second pillar*. This is typically organized in form of deferred compensations, where employees waive part of their salary in favor of employer-provided retirement benefits. In 2007, benefits from occupational pension plans represented about 8% of total old-age income and accrued to 27% of the retirees (Kortmann K. and Halbherr V. 2009). Private old-age provision as the *third pillar* involves additional accumulation of assets like investment funds, shares, real-estate, private pension insurance and life insurance that can be depleted during retirement. From 2002 and 2005 on, the third pillar also includes the state-subsidized Riester- and Rürup pension plans. Overall, the third pillar accounted for 10% of total old-age incomes in 2007 (Kortmann K. and Halbherr V. 2009).[4]

Our analysis of adverse selection in pension insurance focuses on the uptake of private pension insurance within the third pillar because access to private pension insurance is open for everybody and the uptake is purely voluntary. In our definition, private pension insurance includes investment funds within the so-called *Altersvorsorge-Sondervermögen* as their functioning is equivalent to regular private pension insurance. This type of investment fund that was introduced in 1998 is specifically designed for the provision of old age income and underlies a special regulation (see §§ 87–90 of the German Investment Law). Riester- and Rürup pension plans are excluded because of the state subsidies that distort their uptake and the unability to fully control for eligibility for these subsidies with the data at hand.[5]

Anybody is at liberty to purchase a private pension policy to raise retirement income. Individual premiums are generally calculated based on insurance mortality tables by age and gender. While benefits are usually paid out as a monthly pension, most insurance companies offer the option of a single lump-sum payment, instead. In both cases, a minimum benefit is guaranteed, while any profit bonus is uncertain and depends on the development of the capital market. Insurance companies offer various supplemental agreements for the standard policy, mostly related to dependants' protection. In a standard contract, pensions are paid until the policyholder dies. In order to avoid highly negative returns of investment, guarantee periods, survivor's pensions or contribution refund in case of early death can be agreed upon with the insurer. These additional agreements all come at some cost in the sense of lower pensions for a given monthly contribution. Finally, it should be noted that redemption of a purchased

[4] The remaining part of total gross old-age income that is not accounted for by the three pillars is income from employment during retirement.

[5] The coexistence of subsidized and non-subsidized private pension products raises the question why anybody takes up a non-subsidized product while a subsidized one is available. The main reasons are: (i) a number of people are not eligible for the Riester subsidies like e. g. most self-employed, marginally employed, students, social welfare recipients and people receiving disability benefits (see § 10a of the German Income Tax Act for the rather complex eligibility criteria), (ii) subsidies do not automatically imply a high rate of return if the general contract conditions are disadvantageous (Kleinlein, 2011) (iii) under the current legislation, Riester products are unattractive for those who intend to spend their retirement abroad as they would have to pay back the subsidies in that case and finally, (iv) in particular right after the introduction of the Riester pensions, the closing of a contract was accompanied by a heavy administrative burden for the insurant (Oehler, 2009).

policy is financially highly disadvantageous, since contributions for the first years are used to cover broker remuneration and administrative expenses.

2.4 Empirical analysis of insurance determinants

We now investigate the determinants of private pension insurance demand of German households in a probit model. Section 2.4.1 describes the data and the derived variables. The methodology is explained in Section 2.4.2 that also contains estimation results.

2.4.1 Data and derived variables

The cross-sectional data in use is the 2005 wave of the German SAVE study consisting of 2305 households. SAVE is a nationally representative survey of German households held by the Mannheim Research Institute for the Economics of Aging (MEA). With the main focus on savings behavior, financial assets and old-age provision, the survey also includes data on demographic, economic and psychologic characteristics of households. A first experimental wave was launched in 2001. From 2005 on, SAVE is an annually conducted panel of more than 2000 households.[6]

We choose the level of the analysis to be the household because we view old-age provision as a household and not an individual task. Furthermore, the data only contains information on insurance contracts of households and does not allow to distinguish between different policyholders within households. Our attention is restricted to non-retired households where neither the head nor the spouse has retired because old-age provision occurs before retirement. The dependent variable PPI in our probit regression is a binary variable indicating whether a household holds a private pension insurance policy in 2005.[7] Independent variables are grouped into i) the theoretically motivated explanatory variables life expectancy, risk and time preferences, ii) control variables for substitutive old-age provision and financial literacy and iii) control variables for other household socioeconomic characteristics.

We base our analysis on the 2005 wave for two main reasons: First, this wave exclusively contains relevant information on risk attitudes and time preferences. Second, uptake of the alternative state-subsidized Riester pensions introduced in 2001 was low until 2005, but gained momentum from that year on when the Retirement Income Act greatly facilitated the subsidy procedure (BMAS, 2008). As the data constraints do not allow us to fully control for subsidy eligibility, we restrict the sample to the 2005 wave where Riester uptake is still low and thus, demand for private pension insurance

[6] Details on the the design of the SAVE study can be found in Schunk, 2007, and Börsch-Supan et al., 2008a. Item nonresponse in SAVE is adressed by an iterative multiple imputation procedure using a Markov chain Monte Carlo algorithm. Provided a properly performed imputation, regression based on multiply imputed data leads to efficiency gains and avoids potential biases from systematic nonresponse. We will therefore take advantage of the five imputed data sets for SAVE 2005 provided by MEA. For further information on the imputation procedure used in SAVE see Börsch-Supan et al., 2008a, Schunk, 2008, and Ziegelmeyer, 2009, 2011.

[7] The precise wording in the survey is "Other contractually agreed private pension scheme, e. g. investment funds geared specifically to the provision of pension cover, private pension insurance policies which are not promoted by the state or which were taken out before such support was available."

should be still rather unaffected.

The original sample size reduces to an estimation sample of 1320 households due to the following exclusion rules: First, only non-retired households where neither the head nor the spouse has retired are considered (836 observations). Second, we drop households with inconsistent estimates of individual life expectancy, where the indicated average life expectancy of people of their age and sex is less than current age (5 observations). Third, all households with a missing value for the dependent variable PPI are excluded (144 observations).[8] 16% of the final estimation sample hold a private pension insurance.

i) Life expectancy, risk aversion and time preference

Average subjective life expectancy per household is calculated in three steps. First, respondents are asked to estimate average life expectancy of men and women of their age group ($AVLE_{male}$ and $AVLE_{female}$). Second, they indicate the number of years they expect themselves to deviate from the average life expectancy of people of their sex and age ($EXPYEARSDEV_{head}$). Also, they indicate the number of years they expect their partner to deviate from the average life expectancy of his/her sex and age ($EXPYEARSDEV_{spouse}$). Subjective life expectancy for the household head is implicitly given by this information and can be calculated as $SLE_{head} = AVLE_{(fe)male} + EXPYEARSDEV_{head}$. Calculation of subjective life expectancy for the spouse relies on two (weak) assumptions: first, sex of the spouse is assumed to be opposite to the one of the head, and, second, age of the spouse is assumed to be about the same as the one of the head.[9] [10] It is then given by $SLE_{spouse} = AVLE_{(fe)male} + EXPYEARSDEV_{spouse}$. Average subjective life expectancy for partner households is finally derived as $AVSLE = (SLE_{head} + SLE_{spouse})/2$.

Risk attitudes and time preferences of the household head are indirectly inferred from hypothetical choices inquired in the survey. Table 2.1 displays the two sets of options that are used for their derivation. In the first set, people are requested to choose between options A and B in three different hypothetical lotteries. A is always a certain zero, while B implies a 50% chance of loosing 100 € and a 50% chance of winning 200 €, 300 € and 400 €, respectively. $RISKAVERSE$ is a dummy variable

[8]We exclude observations with an imputed dependent variable for two reasons; first, estimation efficiency and second and more importantly, robustness to problems with the underlying imputation model (see HIPPEL, 2007 for a discussion of imputed dependent variables in regression analysis.). However, to verify insensitivity of the results to the inclusion of cases with missing dependent variable, we provide estimation results including these observations in Table A.4 in the appendix.

[9]We view even the latter assumption as non-critical, since, on average, the household head is only 0.17 years older than his or her spouse in the 864 partner households with a standard deviation of 5.31 years.

[10]In a similar manner, BROWN, 2001, BROWN et al., 2008a, and INKMANN et al., 2011, refer to individual expected survival probabilities. Data limitations force most other studies to make either use of aggregate mortality tables or the less nuanced self-assessed health status as a proxy.

that is equal to one for the most risk averse individuals who always opt for A, even in the third lottery where potential payment in B is highest. This is the case for 65% of our sample.

First Set		1	2	3
A	100%	0	0	0
B	50%	-100	-100	-100
	50%	200	300	400
Second Set		1	2	3
A	now	-800	-800	-800
B	in 10 months	-825	-870	-990
Source: The German SAVE study 2005.				

Table 2.1: Hypothetical choices to elicit risk and time preferences

In the second set, the hypothetical choice is not between certain and uncertain payments, but between payments at different points in time. In each scenario, A is an immediate payment of 800 €, while B is a payment of 825 €, 870 € and 990 € in 10 months. $IMPATIENT$ is a dummy variable that is equal to one for the most impatient individuals that always opt for paying in 10 months even if the postponed payment is highest.[11] 11% of the sample are classified as impatient here. We are only able to infer preferences of the household head, but not of the spouse which, however, is less a concern since the head states to be involved in financial decision-making in 95% of all cases.

ii) Financial literacy and substitutive old-age provision

Since old-age provision is a complex matter that requires a certain degree of knowledge in financial affairs, we account for the financial literacy of households by their stock market participation. More precisely, $FINLIT$ is a dummy variable indicating whether the household holds equity and real-estate funds or other financial assets like equity bonds, discount certificates, hedge funds, wind power funds, film funds and other financial innovations. Stock market participation is an appropriate proxy for financial literacy as investment in this type of assets reveals a certain level of financial

[11] Comparable measures for risk aversion based on hypothetical lottery choices inquired in surveys are used by Brown et al., 2008a, and Salm, 2010. Cutler et al., 2008, furthermore suggest indicators like drinking and smoking behavior, job-based mortality risk, preventive care and the use of seat belts that are also frequently used. An analogous measure of time preference is derived by Brown et al., 2008a, from an experimental module in the 2004 HRS. Other studies rely on the length of the financial planning horizon to proxy for time preferences (Brown et al., 2008a, and Salm, 2010).

sophistication (Van Rooij et al., 2011).[12] [13]

As private pension insurance is only one component of overall old-age provision, we need to take into account expected benefits from the first and second pillar as well as other types of third pillar old-age provision like real estate property, Riester pension plans, equity funds etc. We use the type of employment of the main earner in order to approximate the expected benefit level from the first pillar of the old-age provision system due to the previously noted substantially varying benefit levels by type of employment. Employment is classified in four categories: civil servant ($CIVSERV$), white/blue-collar worker ($WORKER$), self-employed ($SELFEMPL$) and unemployed ($UNEMPL$).

Part of the population is eligible to occupational pension schemes and the government-subsidized Riester pension plans. We control for benefits from these sources by a variable containing the end of December 2004 balances of occupational pension schemes and Riester contracts ($OTHINS$). We also control for private wealth, separately for financial wealth and other rather illiquid types of wealth. $FINWEALTH$ is the sum of all net financial assets excluding pension insurance in 1000 €. $OTHWEALTH$ contains all other types of net wealth, i.e. business property, real property and other assets in 10000 €. In some estimation specifications, these types of substitutive old-age provision are adjusted by equivalence scales to account for differing financial needs of single and partner households ($FINWEALTHEQ$, $OTHWEALTH$, $OTHINSEQ$). We divide insurance balances and wealth by 1.5 for partner households following the modified OECD equivalence scale that assigns a weight of 0.5 to the second adult in a household. Additionally, we include the squared equivalence scale adjusted wealth ($FINWEALTHEQ2$ and $OTHWEALTH2$) to take possible nonlinear effects into account.

iii) Socioeconomic characteristics

Finally, we control for households' socioeconomic characteristics that we assess to be relevant for the insurance choice. Average age, AGE, is supposed to represent the maturity status of the household in its life cycle. $AGE2$, the squared average age, is

[12] The related empirical literature uses various other measures to capture financial literacy. Brown, 2001, and Inkmann et al., 2011, rely on the general education level, while Mottola and Utkus, 2007, gather from demographic characteristics to financial experience. Yet others use contact with tax advisors (Börsch-Supan et al., 2008b) or create indices by dint of direct investigations in surveys (Agnew et al., 2008, Brown et al., 2008a, and Bucher-Koenen, 2009).

[13] From 2007 to 2009, SAVE contains quiz-like questions to capture the respondents' financial literacy. Assuming financial literacy to be constant over time and applying this measure to households for which it is available, however, would result in a loss of sample size of about 30%. Instead, we use these later waves to validate our proxy: Correlations between stockmarket participation and correctness of answers to the financial literacy questions are substantial and highly significant. For instance, the tetrachoric correlation between stockmarket participation and a binary variable indicating three out of three correctly answered questions lies between 0.4 and 0.5 depending on the wave and is significantly different from zero at levels of less than 0.001.

included to allow for a possible nonlinear effect of age. $PARTNER$ is a dummy variable designed to distinguish partner and single households. Alternatively, we include $MARRIED$ that identifies married respondents. $NRCHILD$ equals the number of children and stepchildren of the head and his spouse.[14] $EAST$ is a dummy variable that characterizes households located in Eastern Germany. $INCOME(EQ(2))$ is the net (equivalent(squared)) income of the household that should control for its purchasing power and possible nonlinear effects.[15]

Generally note the following: We observe holdings of private pension insurance and household characteristics in 2005 or end December 2004. Theory suggests that starting from a situation without an insurance policy, a household implicitly calculates his net benefit from buying insurance in any given period. If this benefit is positive, the household buys a private pension insurance policy. In consecutive periods, the problem changes into the one of keeping or selling the previously bought policy. Selling a policy implies a financial loss due to administrative expenses. A critical point in our analysis is that we are unable to distinguish between new and old policyholders. Hence, there might be households in our sample that keep a policy though they would not buy it if they could newly decide in 2005. It would therefore be meaningful to run a similar analysis on the uptake of private pension insurance policies with panel data which, however, requires a larger sample size and a stable panel structure. Means of the variables and their correlations for the estimation sample are given in Tables 2.2 and 2.3.

2.4.2 Estimation and results

To estimate determinants of private pension insurance uptake, we specify a probit model with the dichotomous dependent variable PPI_i for all households $i = 1 \ldots N$. PPI_i takes the value one for households holding a private pension insurance policy in 2005. As usual, we estimate the probit model by maximum-likelihood estimation. To deal with item non-response, we take advantage of the five multiply imputed data sets provided by MEA and combine the separate complete-data results by the method known as *Rubin's Rule*. This method averages estimated coefficients across datasets

[14] The presence of children is accounted for to capture a possible bequest motive in old-age provision (Hurd, 1987, Bernheim, 1991, Johnson et al., 2004, Börsch-Supan et al., 2008b, and Inkmann et al., 2011). Yet other authors rely on self-reported importance of bequest motives (Brown, 2001) or the existence of a will or trust (Brown et al., 2008a).

[15] In contrast to the substitutive old-age provision where we only adjust for a partner, we also account for children when calculating net equivalent income. The reason is that the ability to pay insurance premiums from current income depends on the presence of children, whereas retirement income typically only serves the financial needs of the parents. Calculation of net equivalent income of a household conceptually again follows the modified OECD equivalence scale. Some specifications contain the net equivalent income, others the unadjusted net income. We also considered an alternative income measure roughly adjusted for subsistence income as defined by the Hartz IV regulations which, however, left our results unaffected.

	Estimation Sample N=1320		**PPI=1** N=206 (16%)		**PPI=0** N=1114 (84%)	
Variable	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
AVSLE	78.85	7.55	80.12	7.01	78.62	7.63
RISKAVERSE*	0.65	0.48	0.66	0.47	0.65	0.48
IMPATIENT*	0.11	0.32	0.06	0.24	0.12	0.33
FINLIT*	0.22	0.41	0.39	0.49	0.19	0.39
UNEMPL*	0.22	0.42	0.07	0.26	0.25	0.43
CIVSERV*	0.06	0.23	0.08	0.28	0.05	0.23
WORKER*	0.62	0.48	0.67	0.47	0.62	0.49
SELFEMPL*	0.09	0.29	0.18	0.39	0.08	0.27
AGE	40.41	11.12	40.29	8.87	40.43	11.48
NRCHILD	1.50	1.32	1.42	1.16	1.51	1.35
PARTNER*	0.63	0.48	0.74	0.44	0.61	0.49
MARRIED*	0.57	0.50	0.65	0.48	0.56	0.50
EAST*	0.32	0.47	0.33	0.47	0.32	0.47
FINWEALTHEQ	1.73	14.84	2.92	6.91	1.51	15.83
FINWEALTH	2.44	22.18	4.10	9.86	2.14	23.71
OTHWEALTHEQ	10.08	53.32	11.57	34.00	9.82	55.75
OTHWEALTH	14.01	77.77	16.70	50.82	13.53	81.17
INCOMEEQ	1362.52	1576.31	1745.27	2413.73	1294.35	1365.06
INCOME	2305.68	2638.93	2970.89	3366.59	2187.20	2470.17
OTHINSEQ	1862.82	7881.20	3454.93	11322.42	1579.26	7062.55
OTHINS	2625.38	10998.41	4885.96	15799.32	2222.77	9854.25

Note: Sample means are weighted using sample weights and averaged over the five datasets. Variables marked with * are dummy variables.
Source: The German SAVE study 2005. Own calculations.

Table 2.2: Sample means of dependent and independent variables by private pension insurance holdings

	AVSLE	RISK-AVERSE	IMPATIENT	FINLIT	UNEMPL	CIVSERV	WORKER	SELF-EMPL	AGE	NRCHILD	PARTNER
AVSLE	1										
RISKAVERSE	-0.03	1									
IMPATIENT	-0.01	-0.07	1								
FINLIT	0.07	-0.03	-0.12	1							
UNEMPL	-0.07	-0.04	0.16	-0.18	1						
CIVSERV	0.00	0.01	-0.06	0.10	-0.13	1					
WORKER	0.01	0.01	-0.11	0.07	-0.69	-0.32	1				
SELFEMPL	0.08	0.03	-0.01	0.06	-0.17	-0.08	-0.42	1			
AGE	-0.06	0.10	-0.05	0.07	-0.11	0.08	0.02	0.07	1		
NRCHILD	-0.02	0.11	0.05	-0.01	-0.08	0.03	0.06	-0.01	0.42	1	
PARTNER	0.02	0.06	-0.07	0.20	-0.31	0.05	0.17	0.12	0.22	0.34	1
MARRIED	-0.04	0.09	-0.10	0.17	-0.27	0.05	0.17	0.05	0.31	0.36	0.78
EAST	-0.06	-0.03	0.07	-0.11	0.14	-0.10	-0.06	-0.01	0.05	0.04	-0.09
FINWEALTHEQ	0.03	0.03	-0.03	0.14	0.01	0.01	-0.03	0.03	0.06	-0.02	0.05
FINWEALTH	0.02	0.03	-0.03	0.14	0.01	0.01	-0.03	0.03	0.06	-0.01	0.06
OTHWEALTHEQ	0.02	0.03	-0.04	0.09	-0.02	0.00	-0.04	0.09	0.05	0.02	0.06
OTHWEALTH	0.02	0.02	-0.03	0.09	-0.02	0.00	-0.04	0.09	0.06	0.03	0.08
INCOMEEQ	0.02	-0.01	-0.09	0.19	-0.19	0.12	0.03	0.12	0.19	0.06	0.20
INCOME	0.02	0.00	-0.09	0.21	-0.21	0.11	0.05	0.13	0.18	0.18	0.33
OTHINSEQ	0.05	-0.03	-0.04	0.24	-0.11	-0.04	0.06	0.08	0.11	0.04	0.09
OTHINS	0.05	-0.03	-0.04	0.24	-0.11	-0.04	0.06	0.09	0.11	0.05	0.12

	MARRIED	EAST	FINWEALTH-EQ	FINWEALTH	OTHWEALTH-EQ	OTHWEALTH	INCOME-EQ	INCOME	OTHINS-EQ	OTHINS
MARRIED	1									
EAST	-0.09	1								
FINWEALTHEQ	0.06	-0.05	1							
FINWEALTH	0.07	-0.04	1.00	1						
OTHWEALTHEQ	0.07	-0.07	0.62	0.63	1					
OTHWEALTH	0.08	-0.07	0.64	0.64	0.99	1				
INCOMEEQ	0.17	-0.14	0.14	0.12	0.11	0.12	1			
INCOME	0.28	-0.15	0.14	0.13	0.13	0.14	0.94	1		
OTHINSEQ	0.12	-0.10	0.13	0.12	0.13	0.14	0.31	0.30	1	
OTHINS	0.14	-0.10	0.13	0.12	0.14	0.15	0.27	0.29	0.99	1

Source: The German SAVE study 2005. Own calculations.

Table 2.3: Correlations of the independent variables weighted by sampling weights and averaged over the five datasets

and takes within-imputation and between-imputation variances into account when calculating standard errors of the estimates (Rubin, 1987).

We distinguish between a model with purely theory-led explanatory variables and six different specifications where vectors of previously derived control variables X_i are included. The underlying latent model is thus specified as

$$PPI_i^* = \beta_1 + \beta_2 AVSLE_i + \beta_3 RISKAVERSE_i + \beta_4 IMPATIENT_i (+X_i\beta) + \varepsilon_i. \quad (2.1)$$

Table 2.4 displays average marginal effects calculated using Rubin's Rules for multiply imputed data for the model without control variables and six different specifications with control variables.[16] Let us first consider the model without control variables. As illustrated in the first column of Table 2.4, estimation results closely correspond to our expectations. In particular, average subjective life expectancy significantly positively influences the demand for private pension insurance. Other things being equal, households who expect to become old, are more likely to purchase supplementary private pension insurance than those who expect to die young. Quantitatively, the effect seems to be small, i. e. if subjective life expectancy increases by one year, the probability of having PPI increases by 0.3 percentage points, but it is statistically significant at a level of 1.3 percent. Risk averse individuals should be more willing to insure their longevity risk and thus exhibit a larger likelihood of having private pension insurance. Correspondingly, the marginal effect of risk aversion on private pension insurance uptake is positive, but insignificant. Since investment in pension insurance postpones today's consumption to tomorrow, individuals with high time preference should buy private pension insurance less frequently than their patient counterparts. As expected, a high rate of time preference is associated with a low predicted probability of having private pension insurance. With a p-value of 0.002, this relationship is highly significant in the model without the vector of control variables.

Now, let us direct our attention to the model specifications with control variables in columns three to eight of Table 2.4. Estimation results for this model prove to be robust across the six specifications. Compared to the model without control variables, our previous results remain qualitatively stable. As before, the probability of having private pension insurance significantly increases with average subjective life expectancy. We therefore conclude that people rationally take expectations about lifetime into account when deciding on old-age provision. Combined with the predictive power of subjective expectations of lifetime, this indicates risk-based selection due to private

[16]Marginal effects can be either evaluated at fixed values of the independent variables, typcially the means, or averaged over all observations. The first are called marginal effects at the mean (MEM), while the latter are referred to as average marginal effects (AME). The main argument in favor of AME is the fact that sample means used during the calculation of MEM might refer to either nonexistent or nonsensical observations (Bartus, 2005). For comparison, we also calculated the MEM which are almost identical to the AME (see Table A.3 in the appendix).

	Without control variables		With control variables (1)		(2)		(3)		(4)		(5)		(6)	
	dy/dx	**P>z**	**dy/dx**	**P>z**	**dy/dx**	**P>z**	**dy/dx**	**P>z**	**dy/dx**	**P>z**	**dy/dx**	**P>z**	**dy/dx**	**P>z**
AVSLE	0.003**	0.013	0.003**	0.036	0.003**	0.043	0.003**	0.037	0.003**	0.044	0.003**	0.034	0.002*	0.091
RISKAVERSE	0.006	0.784	0.007	0.729			0.007	0.730			0.007	0.746	0.000	0.987
IMPATIENT	-0.081***	0.002	-0.043	0.172			-0.042	0.175			-0.041	0.186	-0.042	0.181
FINLIT			0.097***	0.000	0.099***	0.000	0.096***	0.000	0.098***	0.000	0.099***	0.000	0.090***	0.001
CIVSERV			0.173**	0.011	0.185***	0.007	0.175**	0.010	0.186***	0.007	0.176**	0.010	0.187***	0.007
WORKER			0.095***	0.001	0.101***	0.000	0.095***	0.001	0.101***	0.000	0.097***	0.000	0.111***	0.000
SELFEMPL			0.246***	0.000	0.255***	0.000	0.245***	0.000	0.254***	0.000	0.253***	0.000	0.260***	0.000
AGE			0.024***	0.002	0.024***	0.001	0.025***	0.001	0.025***	0.001	0.025***	0.001		
AGE2			-0.000***	0.001	-0.000***	0.001	-0.000***	0.001	-0.000***	0.001	-0.000***	0.001		
NRCHILD			-0.017*	0.055	-0.018**	0.049	-0.018**	0.042	-0.019**	0.037	-0.016*	0.067	-0.017*	0.051
PARTNER			0.024	0.310	0.023	0.320	0.020	0.395	0.019	0.410			0.036	0.119
MARRIED											0.015	0.501		
EAST			0.050**	0.027	0.050**	0.028	0.051**	0.027	0.050**	0.027	0.051**	0.027	0.050**	0.029
FINWEALTHEQ			0.001	0.433	0.001	0.424					0.001	0.434	0.005	0.157
FINWEALTHEQ2													0.000	0.964
FINWEALTH							0.001	0.476	0.001	0.467				
OTHWEALTHEQ			-0.000	0.527	-0.000	0.533					-0.000	0.531	0.001	0.339
OTHWEALTHEQ2													0.000	0.665
OTHWEALTH							-0.000	0.545	-0.000	0.551				
INCOMEEQ			0.000	0.315	0.000	0.299					0.000	0.302	0.000	0.868
INCOMEEQ2													0.000	0.696
INCOME							0.000	0.305	0.000	0.283				
OTHINSEQ			0.000	0.252	0.000	0.259					0.000	0.267	0.000	0.823
OTHINS							0.000	0.206	0.000	0.214				

Note: Dependent variable = PPI, sample size $N = 1320$ (non-retired households), * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: The German SAVE study 2005. Own calculations.

Table 2.4: Average marginal effects using Rubin's Rule for multiply imputed data for the model without control variables and six different specifications of the model with a vector of control variables

information. Hence, our investigation of the German annuity market confirms the common finding that annuity markets are in fact characterized by adverse selection.

The impact of risk aversion on pension insurance is again estimated to be insignificantly positive. Thus, preference-driven selection based on risk aversion does not seem to play a major role in the annuitization decision. This conflicts the emerging literature on propitious or advantageous selection based on risk aversion that emphasizes selection effects driven by risk attitudes instead of riskiness (Hemenway, 1990, De Meza and Webb, 2001). Besides the admittedly noisy proxy, a potential explanation is collinearity of risk aversion and subjective life expectancy. This would hold, if risk aversion increased life expectancy due to more cautious health behavior and if individuals rationally took this effect into account when building their expectations about lifetime. Simple cross-correlation analysis as given in Table 2.3, however, throws doubt on this explanation because the correlation coefficient is close to zero and even slightly negative. Instead, we attribute insignificance of the marginal effect of risk aversion to a framing effect (Brown et al., 2008b). People might view private pension insurance policies as a type of investment rather than insurance. Due to its dependency on the ex ante unknown lifetime, return on investment in private pension insurance policies is relatively uncertain. In this regard, risk averse people should less frequently invest in pension insurance. Our result closely corresponds to Brown et al., 2008a, who use a similar proxy for risk aversion. In most of their specifications, more risk averse people do not exhibit a significantly higher likelihood of taking annuities instead of a lump-sum payment. In contrast, Cutler et al., 2008, find the expected relationship between risk-related behavior and annuitization. Smokers or individuals with risky jobs are less likely to be covered by annuities, whereas individuals that undertake preventive health activities or those who always wear seatbelts are more likely to be covered by annuities.

While it is still estimated to be negative, the marginal effect of time preference on the probability of having private pension insurance becomes insignificant once the control variables are taken into consideration. Using an analogous proxy for time preference, Brown et al., 2008a, also do not detect a robust relationship between time preference and annuity uptake. According to his result, patient individuals tend to be less likely to prefer the annuity over the lump-sum payment which, however, is significant at the 10 percent level in only two out of five specifications. We conclude that the effect is mainly attributed to other characteristics of the household than their time preference. A possible candidate is financial literacy which seems to play an outstanding role in the demand for private pension insurance. The probability of having private pension insurance is about 10 percentage points higher in financially literate than in financially illiterate households which is significant at the 1 percent level. This result is in line with the recent literature on the relationship between financial literacy, retirement planning ability and retirement saving (Lusardi and Mitchell, 2007, 2007, 2011, and Van Rooij et al., 2011) and is also supported by Brown et al., 2008a, and Bucher-Koenen, 2009.

Benefit levels from the first pillar proxied by the type of employment also have substantial explanatory power. With the base category being the unemployed, the marginal effect of a self-employed main earner who is least covered by the public pension system is largest as expected. Thus, pre-existing annuities tend to crowd out private pension insurance uptake which ought to be the case according to Mitchell et al., 1999, and Dushi and Webb, 2004, and is empirically confirmed by Bernheim, 1991. According to our results, the predicted probability also increases with being a worker or a civil servant. There, the marginal effect of being a civil servant exceeds that of being a worker. At first glance, this seems counterintuitive due to the relatively more generous benefit levels for civil servants. An explanation might be a more cautious and provident attitude of civil servants on average that is not covered by other regressors.

On the one hand, wealth, in particular financial wealth, increases the afforability of private pension insurance. On the other hand, it works as a substitute to insurance. Rather surprisingly, the monetary variables of (equivalent) net wealth, balance in other insurance-type old-age provision and household income do not determine insurance demand. Wealthy households run a lower risk of depleting their assets before death so that wealth is theoretically supposed to negatively impact the probability of opting for supplementary private pension insurance. This effect should be particularly pronounced for illiquid assets like housing or business property that reduce the required replacement rate from pension insurance. In contrast, for liquid financial assets a positive impact might dominate due to the increasing affordability of private pension insurance. Actually, the signs of our estimated effects point into these directions. However, in accordance with Börsch-Supan et al., 2008b, Brown et al., 2008a, and Inkmann et al., 2011, we do not find any significant relationship in our data. A likely reason are the opposing effects of increased substitution and increased affordability with rising wealth. In a similar manner, other insurance-type old-age provision can be seen as a substitute to private pension insurance such that a negative relationship is expected again. However, we again do not see evidence of substitution between different sources of old-age income. Instead, ahead thinking households tend to rely on several sources of old-age income. This finding is in line with other studies that also find a positive relationship between participation in alternative old-age provision and uptake of private pension plans (Börsch-Supan et al., 2008b, and Inkmann et al., 2011).[17] Finally, net (equivalent) household income also does not seem to play a role in the uptake of private pension insurance. While Börsch-Supan et al., 2008b, estimate a weakly significant positive impact of income on pension insurance uptake, our result corresponds to Brown et al., 2008a.[18]

[17] Note, however, that Inkmann et al., 2011, only find this for a subsample of stockholders.

[18] Presumably, household income is an important determinant of the amount of insurance purchased because of higher purchasing power and higher standard of living that needs to be insured. In

As the average age of its members increases, a household's probability to purchase private pension insurance increases, but at a decreasing rate. Aggravating population aging and raising awareness of decreasing replacement rates of the public pension system should lead to a larger probability of supplementary pension insurance in young households. The youngest households, however, possibly have not yet fully adressed the matter of old-age provion which explains the observed nonlinearity. Whether the respondent is married or lives in a partner household, does not seem to influence the insurance decision. Thus, we do not find evidence for intra-household risk pooling theoretically suggested by Kotlikoff and Spivak, 1981. In contrast to Brown and Poterba, 2000, who find higher annuity demand among singles than couples, our results correspond to Brown et al., 2008a.

Households in Eastern Germany are more likely to purchase private pension insurance than their Western German counterparts. This might be explained by lower expected public pension replacement rates of the Eastern German population due to less continuous employment biographies and lower average income subject to contribution payments (Krenz and Nagl, 2009).[19] Interestingly, if the number of children increases by one, the probability of having private pension insurance falls by about two percentage points. We interpret this statistically significant effect as evidence for a bequest motive or expected intergenerational transfer from children to their parents during retirement. As mentioned by Bernheim, 1991, children's altruism might function as a "safety net" that makes pension insurance less needed. Our finding corresponds to the empirical results by Bernheim, 1991. However, quite a number of studies does not find an empirical indication of bequest motives in old-age provision (Hurd, 1987, Brown, 2001, Börsch-Supan et al., 2008b, Brown et al., 2008a, and Inkmann et al., 2011).

principal, we could estimate a two-stage model with the amount as the dependent variable in the second stage. Unfortunately, data on private pension insurance premium in force and contributions to the scheme prove to be unreliable such that we restrict our attention to the binary variable PPI.

[19] For a detailed income decomposition of the German elderly in the Old and New Laender see Bönke et al., 2010.

2.5 Conclusion

We investigate determinants of private pension insurance uptake of German households using the 2005 SAVE survey on savings and old-age provision. In a comprehensive assessment of the relevant factors suggested by theory and previous empirical work, we simultaneously estimate their importance in a multivariate framework. Our main finding is that households take advantage of private information on expected lifetime in the pension insurance choice. Conditional on other relevant variables, households expecting to become old, are relatively more likely to take up supplementary private pension insurance. More precisely, the probability of having supplementary private pension insurance increases by about 0.3 percentage points with each additional year of expected lifetime. This indicates the presence of adverse selection in the German annuities market.

We also find financial literacy and pre-existing annuities to play a prominent role in the insurance decision. Financially literate households, identified by their active participation in the stock market, are significantly more likely to hold private pension insurance policies. Pre-existing annuities from the quantitatively most important public pension system, tend to crowd out private insurance. Civil servants and workers are less likely to have supplementary private insurance than households with a self-employed main earner who are typically not covered by the public system, though this difference is significant only for the case of the workers. In addition, the number of children is negatively related to the probability of private pension insurance. This can be interpreted as an indication of bequest motives or expected intergenerational altruism. According to our results, uptake of private pension insurance does not differ between single and partner households.

In addition, we only find very limited evidence for the theoretically suggested importance of risk aversion and time preference. Our measure of risk aversion has no explanatory power in the pension insurance choice. This might be explained by the fact that a pension policy cannot only be seen as insurance, but also as a type of investment. On the one hand, the insurance character of private pensions that protects the insurant from longevity risk should be appreciated by risk averse households. On the other hand, the relatively uncertain return on a pension policy that depends on the ex ante unknown length of life tends to retain risk averse households from purchase. These two opposing effects might therefore explain the lacking explanatory power of our measure of risk aversion. Time preference has the expected negative coefficient, but it becomes insignificant as control variables are taken into account.

This work contributes to the literature on adverse selection in annuities markets. Our result is in line with a number of related studies primarily focusing on the UK and US that also find evidence for adverse selection in annuities markets. While most of these studies make use of the money's worth concept to detect adverse selection, we use micro level data and approach the issue from the perspective of the insurant. To our knowledge, we are the first to investigate adverse selection in the German annuities market at the household level. From the policy point of view, our work suggests that the private pension insurance market is in fact characterized by inefficiencies related to adverse selection. Difficulties arise for low risk individuals for whom insurance in the private pension market is prohibitively expensive. Policy makers should therefore keep in mind that privately insuring longevity risk is not without difficulty for part of the population.

For future research, it would be meaningful to conduct a comparable analysis using panel data that allows to observe household characteristics directly at the time of annuity purchase. Since our indicators of risk and time preferences are rather rough, we additionally consider it worthwhile to construct more sophisticated measures of preferences in surveys. This would provide deeper insight in preference-driven selection in insurance markets. Finally, it would be interesting to follow the development of the German pension system and address to adverse selection in Riester pension plans. While cautiously demanded in the beginning, holding of these increased to about 14 million contracts in end of 2010. Possibly, the design of the subsidy scheme that strongly incentivizes specific parts of the population to take up Riester plans, outruns the importance of life expectancy for profitability of the policies and thus reduces adverse selection.

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Chapter 3

Choice under Risk: Experimental Evidence from Ethiopia

3.1 Introduction

The present paper studies risk preferences of small-holder farmers in a developing country. We move beyond a pure investigation of risk attitudes in the tradition of Holt and Laury, 2002, but more generally inquire the structure of risk preferences. In particular, we experimentally test whether choices under risk are consistent with the predictions of expected utility theory and the criterion of first-order stochastic dominance.

Expected utility theory is the dominant theory of decision making under risk in economics. It relies on a set of axioms -completeness, transitivity, continuity and independence- that define a rational decision maker (Neumann and Morgenstern, 1944). We test for consistency of choices with the independence axiom imposed in expected utility theory using a common ratio version of the Allais paradox. The common ratio problem is an experimental design developed by Allais, 1953, based on observed choices over two pairs of lotteries. The first choice is used to infer the individual risk attitude. The second choice then provides a test of consistency with the property of ratio independence implied by expected utility theory (Harrison et al., 2003). There is considerable evidence from the developed world that subjects behave less risk averse in the second choice problem than in the first. This common ratio effect is a systematic property of individual behaviour which, however, cannot be explained by expected utility theory (Camerer, 1995).

First-order stochastic dominance is a rational principle of decision making that posits that stochastically dominating gambles are preferred over stochastically dominated gambles. A gamble A first-order stochastically dominates a gamble B if for any monetary outcome x, A gives an at least as high probability of receiving at least x as B does, and for some x, A gives a higher probability of receiving at least x. Expected utility theory as well as various other descriptive decision theories like rank-dependent expected utility theory and cumulative prospect theory predict consistency of choices with the property of stochastic dominance (Birnbaum, 1999b). In contrast, configural weight theory, the most prominent theory of decision making under risk with non-linear weighting of probabilities in the psychological literature, implies violations of this property (see Birnbaum and McIntosh, 1996).

While studies of risk aversion in developing countries are numerous (Binswanger, 1980, 1981, 1982, Henrich and McElreath, 2002, Humphrey and Verschoor, 2004, 2004, Harrison et al., 2009, Akay et al., 2011, and Hardeweg et al., 2011), only few studies address the descriptive adequacy of expected utility theory in developing countries. Exceptions are the studies of Humphrey and Verschoor, 2004a and Harrison et al., 2009 that comprehensively analyze violations of expected utility, but do not consider first-order stochastic dominance. Altogether, their results are similar to what has been observed in experiments with students in industrialized countries. The authors conclude that expected utility theory does not appropriately describe behavior, but non-linear weighting of probabilities has to be considered in order to organize the data.

Similarly, it has been extensively studied, how risk aversion varies with sociodemographic characteristics (see e.g. Harrison et al., 2007), but empirical evidence on the relationship between sociodemographic characteristics and violations of expected utility theory or stochastic dominance is very rare. The study by Huck and Müller, 2012, provides a recent contribution on the sociodemographic covariates of the Allais paradox using a representative sample from the Netherlands. They find that education, income and asset holdings are related with violations of expected utility theory. We are not aware of a comparable study considering sociodemographic covariates of such behavioral patterns in a developing country.

We contribute to the literature by investigating consistency of decision making of poor subjects in a developing country with expected utility theory and stochastic dominance and the influence of sociodemographic characteristics of the subjects on their decision making. Our research objectives are twofold. First, we aim to assess whether violations of expected utility theory in the form of a common ratio effect and stochastic dominance observed in the developed world carry over to a sample from the developing world. Second, we want to investigate which personal characteristics are correlated with violations of expected utility theory and stochastic dominance. We put special emphasis on the relationship between the educational level of the subject and violation rates because recent studies suggest that a range of behavioral biases are correlated with cognitive abilities (Burks et al., 2009, Dohmen et al., 2010, Benjamin et al., 2012, Huck and Müller, 2012).

For these purposes, we combine experimental tests with high monetary stakes with a survey capturing sociodemographic characteristics of small-holder farmers from

Ethiopia. The paper is organized as follows. Section 3.2 describes the general setting, the design of the experimental tasks and how they were embedded in the survey. Section 3.3 provides a descriptive and an econometric analysis of the data. Section 3.4 concludes.

3.2 Experimental design

Our study includes four experimental tasks on individual decision making under risk which were performed by participants to a larger household survey. The experimental tasks involve tests of consistency with expected utility theory and with transparent and non-transparent first-order stochastic dominance as well as a standard elicitation of the risk attitude of the household head following Holt and Laury, 2002 (details see below). We supplemented the experimental tasks with a questionnaire capturing detailed information on individual and household attributes as well as a record of all income generating activities of the household.

The study was conducted based on a sample of Ethiopian small-holder farmers from the East and West Shewa Zones of the Region of Oromia in spring 2011. The sample of farmers was randomly drawn from member lists of twelve agricultural cooperatives in the survey area. In total, we sampled 366 farmers from 23 different communities. Trained and experienced enumerators conducted the experiments and interviews face to face in the local language Oromifa. Completing the questionnaire and the experimental tasks took about 1.5 hours.

In order to continuously draw the respondents' attention and to make the interview diversified and enjoyable for participants we conducted the experiments at two different points in time in the course of the interview. The Holt-Laury elicitation of risk attitudes was conducted after the introductory sections on the household demographics and dwelling characteristics. The common ratio experiment was run almost at the end of the interview, immediately followed by the stochastic dominance questions. All experiments were explained and visually presented in terms of urns containing beads where the color of the bead determines the payoff.

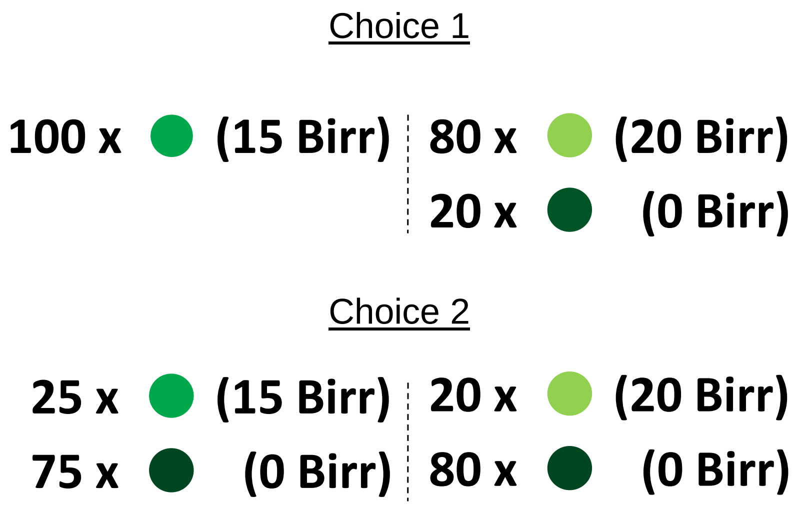
When performing a choice task, subjects were not aware of the fact that additional paid experiments would be performed at later stages. In the Holt-Laury and the common ratio experiments, standard random lottery incentive systems were applied. Choices to be played out for real were determined by the subjects who rolled a ten-sided die in the Holt-Laury experiment and flipped a coin in the common ratio experiment. The stochastic dominance choices were both played for real. Payouts were disbursed in cash immediately upon completion of the interview. The range of possible total payouts was 5-70 ETB with an average total payout of 50 ETB, which amounts to approximately 3 USD. This corresponds to more than a daily wage of an unskilled farm laborer in the area of the study.

3.2.1 Consistency with expected utility theory

We test consistency of preferences with expected utility using a standard common ratio problem. The variant we employ follows Kahneman and Tversky, 1979, and is depicted in Figure 3.1. In the first choice problem, subjects have to chose between a degenerate lottery with a certain payout of 15 and a lottery that gives a payout of 20 with probability 0.8 and a payout of 0 with probability 0.2. Lotteries in the second choice problem are derived from initial lotteries by adding a front end probability of 0.75 of winning zero. That is, the resulting lotteries offer a 0.25 chance of playing the initial lotteries and a 0.75 chance of winning zero. Because the second choice is derived from the first by multiplication with a common ratio from the interval $(0, 1)$, problems of this type are known as common ratio problems (Birnbaum, 1999b).

If we normalize the utility function u such that $u(0) = 0$, an expected utility maximizer chooses the safe lottery in the first choice problem if $u(15) > 0.8u(20)$. Multiplying both sides of the inequality by 0.25 yields $0.25u(15) > 0.2u(20)$. Thus, expected utility theory implies that a subject that chooses the safe lottery in the first choice, also chooses the safe lottery in the second choice and vice versa. The typically observed pattern of choosing safe in the first problem and risky in the second one is, however, incompatible with expected utility theory.

Figure 3.1: The common ratio effect



Note: In each choice problem, we asked subjects to select one out of two transparent bags containing 100 wooden beads of the indicated colors. Legends with monetary values of the different colors and the number of beads of the different colors in the bags were attached to the bags. We used different nuances of a given color within each choice problem to ensure that choices are not driven by cultural meanings of colors or favorite colors.

3.2.2 Consistency with stochastic dominance

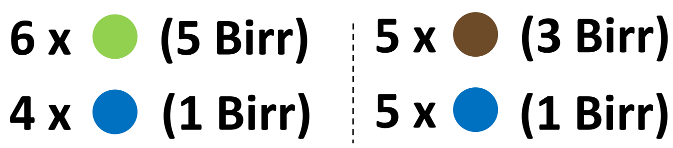
We test consistency of preferences with stochastic dominance using two choice problems. The first offers a transparent dominance relation, the second an intransparent dominance relation following the design of Birnbaum and Navarrete, 1998.

The transparent dominance test is shown in Figure 3.2. The left lottery offers a

0.6 chance of winning 5 and a 0.4 chance of winning 1. The right lottery offers a 0.5 chance of winning 3 and a 0.5 chance of winning 1. It is easy to see that the left lottery dominates the right one as probability and size of the better payoff are higher.

The main purpose of this test is to control whether subjects can process the offered stimuli properly. This seemed particularly important to us in view of the fact that most subjects were unfamiliar with the type of decision problems at hand. The test also serves to control whether subjects are attentive, which, however, can readily be expected given the size of payoffs.

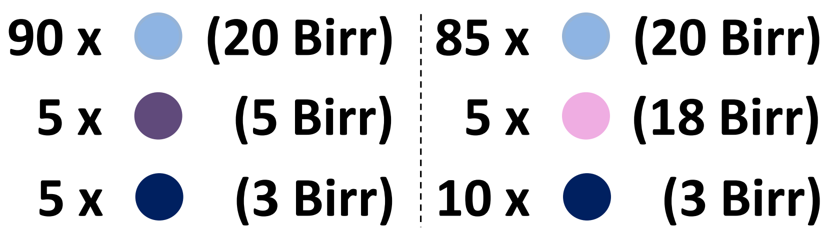
Figure 3.2: Transparent stochastic dominance



The intransparent stochastic dominance test is shown in Figure 3.3. The left lottery (L) stochastically dominates the right lottery (R) as $P(x \geq t|L) \geq P(x \geq t|R)$ for all t, where $P(x \geq t|L)$ denotes the probability that an outcome in lottery L is equal to or exceeds t.

It is also easy to verify that L stochastically dominates R by considering a third lottery A in which you win 20 with a probability of 0.9 and 3 with a probability of 0.1. As L evidently dominates A while R is dominated by A, choosing lottery R constitutes a violation of stochastic dominance.

Figure 3.3: Intransparent stochastic dominance



3.2.3 Risk attitudes

Our experimental elicitation of risk attitudes follows the standard procedure of Holt and Laury, 2002, with ten choices, each between a relatively safe alternative A and a more risky alternative B. In the first choice, the risky alternative B is very unattractive as the probability of winning the high amount (25 Birr $\approx$ 1.50 USD) is very low (0.1). The probability of winning the high amount increases from choice to choice by 0.1 until it amounts to one in the last choice, so that B dominates A in the last choice (see Table 3.1; expected values in the last three columns were not shown to subjects).

The point at which a subject switches from the safe lottery A to the risky lottery B allows inferring his coefficient of relative risk aversion. A higher number of safe choices corresponds to a higher degree of risk aversion (see Holt and Laury, 2002, for details). A risk neutral subject would choose A in the first four rounds and B thereafter. We appropriately scaled payouts used in Holt and Laury, 2002, for our purposes such that they cover the range of payoffs used in the common ratio and stochastic dominance experiments.

Table 3.1: Elicitation of risk attitudes

		A		B				
Choice	$p(x_1)$	x_1	x_2	x_1	x_2	$E[x]_A$	$E[x]_B$	$E[x]_A - E[x]_B$
1	0.1	13	11	25	1	11.2	3.4	7.8
2	0.2	13	11	25	1	11.4	5.8	5.6
3	0.3	13	11	25	1	11.6	8.2	3.4
4	0.4	13	11	25	1	11.8	10.6	1.2
5	0.5	13	11	25	1	12	13	-1
6	0.6	13	11	25	1	12.2	15.4	-3.2
7	0.7	13	11	25	1	12.4	17.8	-5.4
8	0.8	13	11	25	1	12.6	20.2	-7.6
9	0.9	13	11	25	1	12.8	22.6	-9.8
10	1	13	11	25	1	13	25	-12

Note: 16.67 Birr=1 USD.

3.3 Empirical analysis

3.3.1 Descriptive analysis

We start our analysis by looking at the results for the common ratio effect in Table 3.2. About 60% of subjects behave in accordance with expected utility theory by choosing either both times A or both times B. 40% display a common ratio effect which casts doubt on the decriptive adequacy of the independence axiom implied by expected utility theory in our sample. These numbers are in line with previous research in developed countries (see Camerer, 1995, and Starmer, 2000, for recent surveys of the evidence). Existing evidence from developing countries also points to similar violation rates. Using a common consequence version of the Allais paradox, Humphrey and Verschoor, 2004b, observe an overall violation rate of expected utility theory of 64% in a sample from India, Ethiopia and Uganda.

The violations are systematic in the sense that the pattern AB is more frequently observed than the opposite pattern BA. According to the test statistic of Conlisk, 1989, the asymmetry of violations is highly significant (z = 3.95, p < 0.01). The asymmetry of violations is in line with previous results (see e.g. Cubitt et al., 1998, Loomes and Sugden, 1998). It can be explained by the fanning-out hypothesis put forward by Machina, 1982, according to which subjects become less risk averse when moving from dominating to dominated lotteries.

Table 3.2: The common ratio effect

	n	%
AA	93	25.48
BB	125	34.25
AB	97	26.58
BA	50	13.70
	365	100

Our results for the tests of stochastic dominance are presented in Table 3.3. We observe a violation rate of transparent dominance amounting to 7.1%. This rate is only slightly higher than the one usually observed with students in developed countries. For instance, Birnbaum and Navarrete, 1998, report a violation rate of transparent dominance of 4.7% among undergraduate students at an American university. Therefore, we are inclined to conclude that the farmers understood the tasks in our experiments sufficiently well.

55.34% of the sample violate non-transparent stochastic dominance. With a z-score of 2.0414, a binomial test rejects the null hypothesis that the violation rate is 50% in favor of the alternative hypothesis that it is greater than 50% at a significance level of

0.02. We thus conclude that the violation rate of non-transparent stochastic dominance in our sample is significantly greater than 50%.[1] The observed violation rate of 55.34% is roughly in line with previous studies in developed countries and even seems to be somewhat lower. Birnbaum and Navarrete, 1998, report a violation rate of 70%. Birnbaum, 1999, 2000, observe a violation rate of 57.4% in an internet sample and 72.2% in a lab sample.

We conclude that violations of stochastic dominance which are common even amongst highly educated subjects in the developed world also occur in samples of mainly illiterate poor farmers in the developing world. Interestingly, violation rates in the latter do not seem to exceed those in the former as one may have expected.

Table 3.3: Violation rates with expected utility theory and stochastic dominance

	n	%
Violation of expected utility theory	147	40.27
Violation of transparent stochastic dominance	26	7.10
Violation of non-transparent stochastic dominance	202	55.34

Table 3.4 contains the results of the Holt-Laury elicitation of risk attitudes. 326 out of 366 subjects (89%) played consistently and switched only once from the safe to the risky option. This makes us confident that the majority of subjects fully understood the rules of the game, which reinforces our conclusion from the transparent dominance game.

Most subjects switched from the risky to the safe option after at least five safe choices. They are hence generally risk averse. 15.7% of the sample exhibit less than three safe choices and are thus highly risk loving. 39.45% are risk neutral or risk loving.

Compared to the initial study by Holt and Laury, 2002, the degree of risk aversion observed in our sample is relatively low. For high real incentives, Holt and Laury observed altogether only 2% of highly risk loving subjects, 19% of risk neutral or risk loving subjects and a median number of safe choices of six.

The share of nearly 39.45% of risk neutral or risk loving subjects seems also high compared to other studies in developing countries (e.g. Hardeweg et al., 2011) and in particular to the study by Yesuf and Bluffstone, 2009, which as our study elicits risk aversion in rural Ethiopia. However, as pointed out by Vieider et al., 2012, in a study of risk attitudes in 30 countries including Ethiopia, risk-seeking behavior seems to be more frequent than supposed so far.

Observing several choices on the same subject pool allows to compute correlations between them. Table 3.5 shows pairwise correlations between the violation of expected

[1] This is a conservative test. If subjects actually satisfy stochastic dominance, the hypothesis that the individual probability of violating stochastic dominance due to mistakes, boredom or lack of motivation equals 0.5 marks the limit (Birnbaum and Navarrete, 1998).

Table 3.4: Distribution of elicited risk attitudes

Number of safe choices	n	%	Range of coefficient of relative risk aversion
0-1	25	7.67	$\beta < 2.05$
2	26	7.98	$2.05 < \beta < 1.55$
3	35	10.74	$1.55 < \beta < 1.18$
4	42	12.88	$1.18 < \beta < 0.86$
5	81	24.85	$0.86 < \beta < 0.57$
6	60	18.40	$0.57 < \beta < 0.28$
7	36	11.04	$0.28 < \beta < -0.05$
8	19	5.83	$-0.05 < \beta < -0.5$
9-10	2	0.61	$-0.5 < \beta$
	326	100	

utility theory and stochastic dominance and the degree of risk aversion. Apparently, the experimental outcomes are rather unrelated. With the exception of a slightly positive correlation between the degree of risk aversion and violation of non-transparent stochastic dominance significant at the 10 % level, none of the correlation coefficients is significant at conventional levels. These results suggests that violation of the rather widely accepted stochastic dominance principle is unrelated to violation of the controversial independence axiom. Furthermore, observed violations do not seem to be driven by the risk attitude of the subjects.

The latter point is particularly interesting because, as pointed out by Harrison et al., 2003, expected utility theory cannot be reliably tested without controlling for the risk attitude of the subject. This is because the certainty equivalent of a lottery and the difference in certainty equivalents of lottery pairs vary with the degree of risk aversion of a subject. Consequently, the incentive to reveal the actually preferred lottery in a choice problem is not the same for all subjects. With reference to several well-known tests of expected utility theory, Harrison et al., 2003, demonstrate that for plausible levels of risk aversion the difference in certainty equivalents in offered lotteries may collapse to zero. Thus, subjects may be nearly indifferent between lotteries which limits the potential to test the validity of a theory based on observed choices.

Table 3.5: Pairwise correlations

	Violation of EUT	Violation of transp. SD	Violation of non-transp. SD	Risk aversion
Violation of EUT	1			
Violation of transp. SD	0.077	1		
Violation of non-transp. SD	-0.013	-0.073	1	
Risk aversion	-0.039	0.013	0.100*	1

3.3.2 Econometric analysis

We now consider how choices under risk vary with sociodemographic characteristics of the subjects. We are particularly interested in the role of the educational background for violations of expected utility and stochastic dominance.

Using a probit model, we regress a binary variable indicating violation of expected utility theory and, respectively, stochastic dominance on measures of the educational background of the subject:

$$violation_i = \alpha + \beta\, education_i + X_i'\,\delta + u_i$$

where $education_i$ is a variable capturing the educational background of individual i, X_i a vector of control variables and u_i an error term. If more educated subjects have lower violation rates, we expect β to be negative.

We consider three measures of the educational background of the individual. First, we use the highest educational level attained by the subject with the categories 1) no formal education, 2) some or completed primary education and 3) more than primary education. Second, we use a dummy variable that equals one if the subject is able to write. Third, we use a dummy variable that equals one if the subject is able to solve simple math problems, which is assessed based on the correct answer to the following question: "Suppose you want to buy bottles of softdrink in a shop. The shop sells a bottle of softdrink for 4 Birr. How many bottles can you buy if you have 20 Birr?" Descriptions and summary statistics of all variables used in the regressions, are given in Tables B.1 and B.2 in the appendix.

Regression results are shown in Table 3.6 which reports marginal effects. Dependent variables are binary variables indicating violations of expected utility (columns 1-3), transparent stochastic dominance (columns 4-6) and non-transparent stochastic dominance (columns 7-9). For each dependent variable, model 1 includes the highest educational level attained, model 2 the ability to write and model 3 the ability to calculate as measures of education.

As displayed in columns 1-3, we find support for the hypothesis that education is linked with violation of expected utility theory. This holds for the formal education variable and the writing ability, while the mathematical ability seems to be unrelated. Interestingly, more educated subjects actually have larger probabilities of violating expected utility theory. More precisely, a subject with some or completed primary education and otherwise average characteristics has a probability of violating expected utility theory that is 57.6 percentage points larger compared to a subject without formal education. Similarly, the predicted probability of violating expected utility theory is 50.7 percentage points larger for a literate subject compared to his illiterate counterpart. This finding contradicts the result by Huck and Müller, 2012 who, depending on the treatment, find either no role of education or a negative effect of education on violating expected utility theory.

In line with Huck and Müller, 2012, we do not observe any age effects. Controlling for other characteristics, personality traits like trustfulness, optimism and risk aversion have no significant influence on the probability of violating expected utility theory. As in Huck and Müller, 2012, the household income category is not statistically significantly related with the violation probability. Among the variables capturing household wealth, i.e. size of land holdings, ownership of radio or mattress, only the latter has a statistically significant positive influence.

Considering violation of stochastic dominance in columns 4-9, we first observe that the educational background does not seem to play a role. This is somewhat surprising given that related studies from the western world have found that the probability of choosing stochastically dominated lotteries decreases with education (Birnbaum, 1999a). We consistently find that more optimistic subjects have a larger probability of violating stochastic dominance. For the case of transparent dominance, this also holds for trusting compared to more skeptical subjects and subjects with a household income from the second compared to the first tercile. Again, the age of the subject does not matter and so does household wealth. For non-transparent stochastic dominance, we observe a significantly negative influence of the household size and asset ownership.

In sum, the power of sociodemophraphic characteristics in explaining experimental choices is rather limited in our sample. More educated subjects tend to violate expected utility theory more frequently, while we do not observe a relationship between education and stochastic dominance. Throughout, we do not find significant effects of individual risk attitudes on experimental choices. In line with Harrison et al., 2003, we thus conclude that violations of the properties under consideration are not driven by low or zero opportunity costs of making decision errors for risk averse individuals. However, our results suggest that other psychological traits of decision-makers such as their trustfulness or optimism are revelant for explaining choices under risk.

Table 3.6: Regression results for the violation of expected utility theory and first-order stochastic dominance

	Violation of EUT (Allais)			Violation of transparent SD			Violation of non-transparent SD		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Some or completed primary education	0.576***			0.434			-0.049		
	(0.176)			(0.297)			(0.171)		
More than primary education	0.331			0.054			0.153		
	(0.281)			(0.588)			(0.279)		
Ability to write		0.507***			0.394			-0.056	
		(0.176)			(0.313)			(0.172)	
Ability to calculate			0.012			-0.158			-0.325
			(0.227)			(0.333)			(0.231)
Age 35-44	-0.171	-0.185	-0.157	0.210	0.149	0.135	-0.267	-0.261	-0.286
	(0.260)	(0.260)	(0.257)	(0.543)	(0.536)	(0.533)	(0.260)	(0.260)	(0.261)
Age 45-54	-0.203	-0.187	-0.288	0.661	0.668	0.502	-0.060	-0.076	-0.120
	(0.282)	(0.281)	(0.279)	(0.548)	(0.543)	(0.532)	(0.281)	(0.282)	(0.282)
Age 55-64	-0.092	-0.131	-0.223	0.089	0.058	-0.052	0.100	0.077	0.029
	(0.286)	(0.281)	(0.279)	(0.585)	(0.576)	(0.569)	(0.288)	(0.285)	(0.286)
Age 65+	0.218	0.194	-0.039	0.704	0.684	0.484	-0.213	-0.248	-0.276
	(0.309)	(0.304)	(0.293)	(0.586)	(0.572)	(0.551)	(0.309)	(0.306)	(0.299)
Trust	0.085	0.098	0.095	0.229*	0.249*	0.229*	-0.054	-0.061	-0.091
	(0.086)	(0.086)	(0.088)	(0.130)	(0.130)	(0.133)	(0.085)	(0.084)	(0.087)
Optimism	-0.583	-0.720	-0.723	1.859**	1.739**	1.715**	1.029**	1.030**	1.009**
	(0.451)	(0.449)	(0.445)	(0.789)	(0.782)	(0.781)	(0.450)	(0.447)	(0.448)
Risk aversion	0.010	0.003	-0.015	-0.033	-0.042	-0.063	-0.041	-0.038	-0.038
	(0.042)	(0.042)	(0.041)	(0.077)	(0.076)	(0.075)	(0.042)	(0.042)	(0.041)
Household size	0.019	0.021	0.015	0.027	0.029	0.023	-0.079**	-0.081**	-0.083**
	(0.034)	(0.034)	(0.033)	(0.057)	(0.056)	(0.056)	(0.034)	(0.034)	(0.034)
Size of own land holdings	-0.036	-0.040	-0.028	0.017	0.020	0.035	0.061*	0.060	0.063*
	(0.037)	(0.037)	(0.036)	(0.055)	(0.055)	(0.053)	(0.037)	(0.037)	(0.037)
Radio ownership	-0.227	-0.235	-0.077	0.061	0.035	0.206	0.051	0.060	0.049
	(0.198)	(0.199)	(0.189)	(0.364)	(0.372)	(0.344)	(0.196)	(0.198)	(0.191)
Mattress ownership	0.395*	0.409*	0.409**	0.799	0.782	0.754	-0.583***	-0.584***	-0.601***
	(0.209)	(0.209)	(0.206)	(0.491)	(0.480)	(0.475)	(0.209)	(0.209)	(0.209)
HH income 2nd tercile	-0.131	-0.131	-0.121	-0.659*	-0.631*	-0.588	-0.052	-0.054	-0.048
	(0.185)	(0.185)	(0.184)	(0.377)	(0.374)	(0.361)	(0.185)	(0.185)	(0.185)
HH income 3rd tercile	-0.175	-0.205	-0.157	-0.155	-0.147	-0.127	-0.257	-0.253	-0.242
	(0.194)	(0.195)	(0.193)	(0.301)	(0.302)	(0.301)	(0.193)	(0.194)	(0.194)
Constant	-0.538	-0.464	-0.140	-4.138***	-4.086***	-3.574***	1.043**	1.090**	1.458***
	(0.498)	(0.489)	(0.546)	(0.995)	(0.967)	(1.036)	(0.497)	(0.491)	(0.558)
Observations	325	325	325	326	326	326	325	325	325
Pseudo R-squared	0.056	0.050	0.031	0.180	0.175	0.166	0.069	0.068	0.072

Results of probit regression. Marginal effects are reported. ***/**/* denote significance at a 1/5/10 per cent level. Standard errors in parentheses.
Omitted categories are no formal education, age interval [20-34] and the first household income tercile.

3.4 Conclusion

This paper focuses on risk preferences of Ethiopian farmers. We combine an experimental study on choice under risk with a survey capturing sociodemographic characteristics of the subjects. The monetarily incentivized experiments include tests of violation of the independence axiom of expected utility theory, transparent and non-transparent stochastic dominance as well as an elicitation of risk attitudes in the tradition of Holt and Laury, 2002.

Two main findings emerge from the present study. First, poor subjects from developing countries seem to behave similarly to (student) subjects from the western world in experimental risky choice situations. Violation rates of expected utility theory in the common ratio problem and rates of selecting stochastically dominated lotteries are comparable to those observed in samples from developed countries.

Second, more educated subjects tend to violate expected utility theory more frequently, whereas we do not observe any relationship with violating the principle of stochastic dominance. We do not observe any consistent pattern regarding the influence of age, income or wealth of the respondent. Sociodemographic characteristics of the subjects thus explain experimental choices only to a limited extent. Our findings suggest, however, that psychological traits of the decision maker like his trustfulness or optimism play an important role.

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Chapter 4

Overconfidence, Performance and Happiness[1]

4.1 Introduction

Many people hold biased beliefs about their own abilities and personal attributes. This bias is typically upward, a phenomenon called overconfidence. The literature is rich in empirical studies of different facets of overconfidence. For instance, individuals are found to overestimate their management skills (Malmendier and Tate, 2005, 2008), their reading comprehension (Maki et al., 2005) or their performance in a college debate tournament (Ehrlinger et al., 2008). In comparison with their peers, individuals tend to overrank themselves resulting in the well-known better-than-average-effect. E.g., Svenson, 1981 reports that 93% of individuals rate their driving skills as above the median. People also underestimate the probability of adverse events such as hospitalization (Weinstein, 1980). Investors overestimate the precision of their knowledge about specific companies (Odean, 1998, 1999). Likewise, confidence intervals elicited in almanac questions like the year of the first flight of the hot air balloon or the length of the Nile River are typically too narrow (Russo and Schoemaker, 1992, Soll and Klayman, 2004), expressing excessive certainty in own beliefs, also called miscalibration.

Psychologists and economists have extensively disputed the benefits and costs of overconfidence. Advocates of overconfidence stress the benefits through increased motivation, aspiration levels and coping ability in the face of negative feedback (Benabou and Tirole, 2002). They relate positive illusions to better mental health, intellectual functioning and interpersonal relationships (Taylor and Brown, 1988, Taylor et al., 2003, Felson, 1984, Isen and Daubman, 1984, Isen and Means, 1983, Bohrnstedt and Felson, 1983). According to the critics, however, overconfidence is costly

[1]This chapter is a slightly modified version of the working paper "Overconfidence, Performance and Happiness" jointly written with Toman Omar Mahmoud and Ulrich Schmidt.

as it results in maladjustment and relational problems (Colvin et al., 1995), disengagement (Robins and Beer, 2001), poorer social skills and lower academic competence (Gresham et al., 2000, Kwan et al., 2008). Overconfidence can cause the pursuit of unreasonable goals (Kahneman and Lovallo, 1993), excessive risk-taking and trading volumes (Odean, 1998, 1999) and excessive business entry (Camerer and Lovallo, 1999).

We contribute to the literature on overconfidence by developing and empirically applying an integrated framework to study the objective and subjective costs of overconfidence during preparation for a future task. We develop a utility-based model to formally derive the effect of overconfidence with regard to existing knowledge during a learning process on final performance and subjective well-being. We show that the erroneous feeling of already mastering a task induces an underestimation of the marginal productivity of subsequent effort. As a result, overconfidence leads to a less than optimal choice of effort and, in turn, to inefficiently low performance. Overconfidence directly lowers utility through inefficient time allocation. In addition, overconfidence inflates performance expectations which contributes to a further loss of utility by widening the gap between expected and actual performance. In sum, we argue that overconfidence is associated with twofold costs as it reduces both objective performance and subjective well-being. The performance loss stems from inefficiently low effort due to an overly positive assessment of existing knowledge. The loss of subjective well-being is a consequence of the performance loss combined with the expectation-inflating effect of overconfidence.

We test these predictions in a natural learning environment of undergraduate students of economics. We measure the overconfidence bias as the number of correctly answered questions in a multiple choice test on the material of an introductory economics course. After completing the test, students were requested to "postdict" their score, i.e. to estimate the number of questions they believed they answered correctly. We define overconfidence as the relative overestimation of the test score, and test for its explanatory power with regard to the final exam score, expected final exam score, and satisfaction with the final exam grade. Consistent with our theoretical predictions, overconfidence is associated with lower exam scores, higher expected exam scores and lower levels of satisfaction.

While evidently important in the setting under consideration, our model is applicable to any process in which investment contributes to the accumulation of a not directly measurable (immaterial) asset required in the future to fulfill a task or reach a goal. Besides learning processes in which effort is invested to accumulate knowledge, other examples include career development, the decision to marry, health behavior, and accumulation of evidence in court.

The remainder of this paper is organized as follows. Section 4.2 reviews the psychological literature and builds the theoretical model. Section 4.3 describes the empirical setting and data. Section 4.4 summarizes the descriptive analysis and regression results. Section 4.5 concludes.

4.2 Why overconfidence might be costly in terms of performance and happiness

4.2.1 Psychological background

Overconfidence affects performance through a change in behavior. In the setting to be studied, we consider the effect of overconfidence on knowledge accumulation through a change in learning behavior. Based on the theory of metacognition, we argue that overconfidence reduces the amount of effort spent during the learning period, resulting in less accumulated knowledge. Less knowledge is not only disadvantageous in itself, but also reduces the subjective well-being of the overconfident individual when knowledge is retrieved.

Metacognition can be defined as "knowing about knowing" or "cognition about cognition" (Metcalfe and Shimamura, 1994). The term has been introduced by Flavell who described metacognition as "one's knowledge concerning one's own cognitive processes and products or anything related to them" (Flavell, 1976, p. 232).

An influential metacognitive theory has been formulated by Nelson and Narens, 1990. Their seminal model of procedural metacognition integrates the large number of studies on metacognition by experimental and educational psychology research that followed Flavell, 1976, and it still represents the scientific base for today's research. Nelson and Narens, 1990, divide cognitive processes into two interrelated levels, the meta level and the object level. The meta level monitors the object level using information about the knowledge status at the object level and controls learning processes at the object level. E.g., as a learner studies, she monitors how well she masters the learning material. The information obtained from monitoring will then be used to control subsequent learning, i.e. to decide whether to terminate or continue learning (Thiede, 1999).

Metacognition has also been studied from a neurocognitive perspective. Neuroscientists link the functioning of metacognitive processes to activity of the human brain. As suggested by dynamic filtering theory, the neural description of Nelson and Narens's model, the interaction of the prefrontal cortex with other cortical regions through feedback loops is responsible for metacognitive monitoring and control processes (Shimamura, 1996, 2000, Fleming and Dolan, 2012).

One implication of Nelson and Narens's, 1990, theory is that a poor monitoring ability adversely affects the overall level of learning achievement. Given a limited time budget, knowing what one does and does not know establishes the basis for efficiently choosing between alternative learning strategies and effort expenditures. It allows avoiding premature termination and prolonged duration of learning and narrowing the focus of learning to deficient areas of knowledge (Hacker et al., 2000). Thus, individuals who are able to accurately monitor themselves should learn more efficiently than their over- or underconfident counterparts, i.e. accomplish more tasks in the same time or the same number of tasks in shorter time.

As regards achievement on a single task, the theory implies that overconfidence with respect to this monitoring task hampers performance as a result of exerting too little effort. If the information obtained from monitoring erroneously points to a sufficient mastery of the subject matter, the study phase will be terminated inefficiently early. Conversely, underconfidence should induce "overlearning" and thus better achievement on this task compared to accurate and, even more, overconfident students.

A learning process results in performance (e.g., an exam grade) as an objective outcome. Performance in turn has affective consequences for the individual which are relevant for future motivation, study habits and dedication to a subject in general (Grimes, 2002). How a person feels about an outcome is not simply a function of the outcome itself, but depends on the standard the person uses for rating success and failure. Emotional experiences are generally enhanced by surprises, so the same outcome can feel very pleasant or very unpleasant depending on the standard. Surprising wins are more elating than expected wins while surprising losses are more disappointing than expected losses (Carver and Scheier, 1990, Carver, 2003, Mellers et al., 1997).

In economics, the most famous theory incorporating this idea is Kahneman and Tversky's, 1979, Prospect Theory. It posits that an outcome is evaluated relative to a reference point, usually considered as the status quo. More recently, Kőszegi and Rabin, 2006, developed a model of reference dependent preferences where the reference point is formed by the expectations of the decision maker. The aspiration's theory of happiness states that individual happiness positively depends on achievement and negatively on the personal aspiration level. The aspiration level can be defined as the smallest outcome deemed satisfactory by the decision maker (Schneider, 1992). Consistently with Kőszegi and Rabin, 2006, expectations about future outcomes have been identified as one important determinant of the aspiration level.[2] Consequently, low expectations tend to offer emotional benefits as they raise joy following success (affective amplification) and reduce pain following failure (affective attenuation).

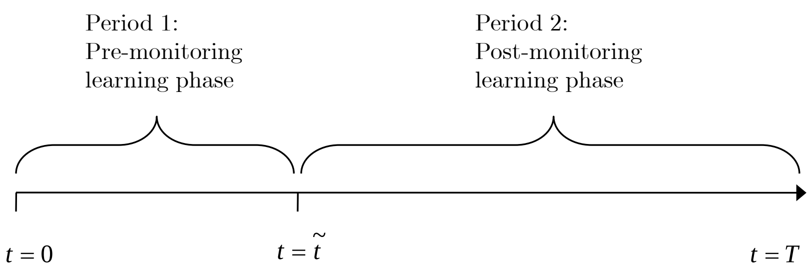
[2]See e.g. Easterlin, 2001, and Frey and Stutzer, 2002a, 2002b, for reviews of the theory of happiness and McBride, 2010, for a discussion of the formation of aspirations. For an early model incorporating the role of expectations for disappointment and elation in evaluating outcomes see Bell, 1985.

4.2.2 Model

We formalize the relationship between metacognitive monitoring accuracy, objective performance and subjective well-being in a utility-based model. Optimal effort spending is derived for an individual who maximizes her utility depending on expected future task performance and leisure consumption. We theoretically show that optimal effort spending decreases with the overestimation of the existing knowledge level. Compared to unbiased self-monitoring, overconfidence implies a reduction of objective performance and final subjective well-being. The loss of subjective well-being results from inefficiently low performance together with inflated performance expectations which simultaneously contribute to a widening gap between expectations and reality.

Our model divides the whole learning period into two phases, the pre-monitoring learning phase and the post-monitoring learning phase. The pre-monitoring learning phase starts at time $t = 0$ and ends at the monitoring time $t = \tilde{t}$ when the knowledge accumulated so far is evaluated. Information gained from monitoring is used to optimize effort spending in the post-monitoring learning phase which ends with final performance at time $t = T$ (see Figure 4.1). In the following, we consider utility-maximizing behavior at an arbitrary monitoring time $t = \tilde{t}$ which may be repeated infinitely often at different times t during the whole learning period.

Figure 4.1: Phases of the learning period



Utility in $t = \tilde{t}$ positively depends on expected future performance $E_{\tilde{t}}[p_T]$ and l_2, leisure consumed in the post-monitoring learning phase:

$$U_{\tilde{t}} = U_{\tilde{t}}(E_{\tilde{t}}[p_T], l_2) \tag{4.1}$$

with $\frac{\partial U_{\tilde{t}}}{\partial E_{\tilde{t}}[p_T]} > 0$, $\frac{\partial^2 U_{\tilde{t}}}{\partial E_{\tilde{t}}[p_T]^2} < 0$, $\frac{\partial U_{\tilde{t}}}{\partial l_2} > 0$, $\frac{\partial^2 U_{\tilde{t}}}{\partial l_2^2} < 0$.

Expected performance is defined as the sum of the current subjective knowledge level $K^s_{\tilde{t}}$ and the expected knowledge gain after monitoring $\Delta K^s_{\tilde{t}}$. $K^s_{\tilde{t}}$ positively depends on effort spent so far in the pre-monitoring learning phase e_1 and ability a. $\Delta K^s_{\tilde{t}}$ decreases with the subjective existing knowledge $K^s_{\tilde{t}}$, and increases with planned future effort in the post-monitoring learning phase e_2 and ability a (see (4.2)).

We explicitly specify one possible overconfidence bias in the model. In particular, we consider the bias in assessing the current knowledge level. We define γ as the extent to which the learner overestimates her existing knowledge level $K_{\tilde{t}}$ at $t = \tilde{t}$, i.e. $K^s_{\tilde{t}} = (1+\gamma)K_{\tilde{t}}$. γ is positive if the learner overestimates her existing knowledge level and negative if the learner underestimates her current knowledge level (see (4.3)).

$$E_{\tilde{t}}[p_T] = K^s_{\tilde{t}}(e_1, a) + \Delta K^s_{\tilde{t}}(K^s_{\tilde{t}}, e_2, a) \tag{4.2}$$

$$= (1+\gamma)K_{\tilde{t}}(e_1, a) + \Delta K^s_{\tilde{t}}((1+\gamma)K_{\tilde{t}}, e_2, a) \tag{4.3}$$

where $\gamma \geq -1$ and $\frac{\partial \Delta K^s_{\tilde{t}}}{\partial e_2} > 0$, $\frac{\partial^2 \Delta K^s_{\tilde{t}}}{\partial e_2^2} < 0$ and $\frac{\partial^2 \Delta K^s_{\tilde{t}}}{\partial e_2 \partial K_{\tilde{t}}} < 0$.
Finally, (4.4) is a time constraint stating that the sum of effort e_2 and leisure l_2 spent in the post-monitoring learning phase must equal the total time budget:

$$e_2 + l_2 = 1. \tag{4.4}$$

Maximizing (4.1) with respect to e_2 and l_2 subject to (4.2) and (4.4) yields the first-order conditions:

$$\frac{\partial \mathcal{L}}{\partial e_2} = \frac{\partial U_{\tilde{t}}}{\partial E_{\tilde{t}}[p_T]} \frac{\partial E_{\tilde{t}}[p_T]}{\partial e_2} + \lambda = 0 \tag{4.5}$$

$$\frac{\partial \mathcal{L}}{\partial l_2} = \frac{\partial U_{\tilde{t}}}{\partial l_2} + \lambda = 0 \tag{4.6}$$

which lead to the optimality condition

$$\frac{\partial U_{\tilde{t}}}{\partial E_{\tilde{t}}[p_T]} \frac{\partial E_{\tilde{t}}[p_T]}{\partial e_2} = \frac{\partial U_{\tilde{t}}}{\partial l_2}. \tag{4.7}$$

According to (4.7), the expected marginal utility of effort equals the marginal utility of leisure in the optimum.
Plausibly, the expected marginal productivity of effort is positive

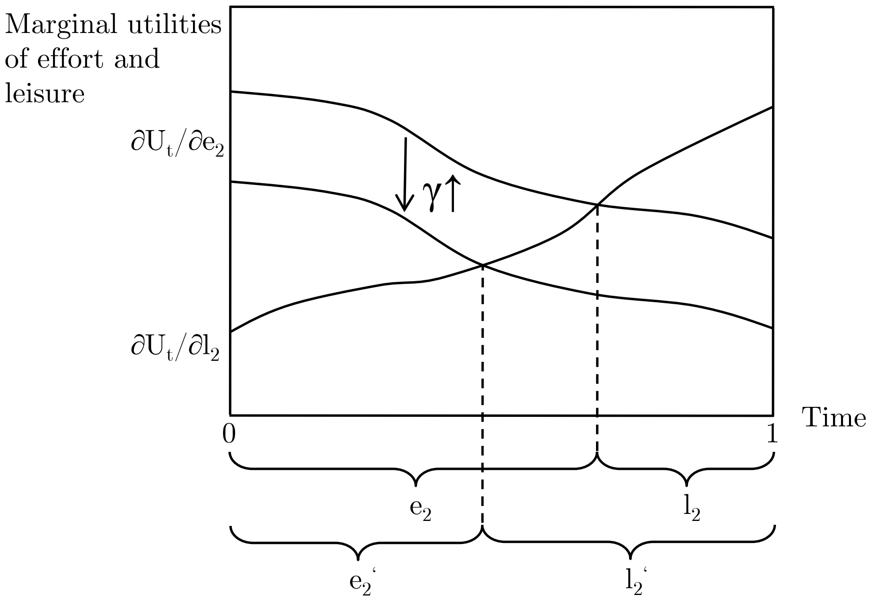
$$\frac{\partial E_{\tilde{t}}[p_T]}{\partial e_2} = \frac{\partial \Delta K^s_{\tilde{t}}((1+\gamma)K_{\tilde{t}}, e_2, a)}{\partial e_2} > 0, \tag{4.8}$$

and can be shown to decrease with the bias γ

$$\frac{\partial^2 E_{\tilde{t}}[p_T]}{\partial e_2 \partial \gamma} = \frac{\partial^2 \Delta K^s_{\tilde{t}}((1+\gamma)K_{\tilde{t}}, e_2, a)}{\partial e_2 \partial K_{\tilde{t}}} K_{\tilde{t}} < 0. \tag{4.9}$$

Thus, an increase in the bias γ reduces the expected marginal productivity of effort in the post-monitoring learning phase and therefore leads to more time spent on leisure and less time spent on effort in the optimal allocation (see Figure 4.2). The more the individual believes she knows already, the less effort she is willing to spend as the expected knowledge gains through effort spending diminish.

Figure 4.2: Change of optimal time allocation as the overconfidence bias increases



As the marginal productivity of effort is positive, lower effort-spending entails lower performance:

$$p_T = K_{\tilde{t}}(e_1, a) + \Delta K_{\tilde{t}}(K_{\tilde{t}}, e_2, a) \tag{4.10}$$

$$\frac{\partial p_T}{\partial \gamma} = \frac{\partial \Delta K_{\tilde{t}}}{\partial e_2}\frac{\partial e_2}{\partial \gamma} < 0. \tag{4.11}$$

So far, we have shown that overconfidence with regard to one's knowledge level during a learning process lowers objective performance. We now address the implications of overconfidence for ex-post subjective well-being. In accordance with the aspirations theory of happiness and related psychological theories, we supplement the ex-ante utility function with the gap between expected and actual performance and specify ex-post utility as

$$U_T = U_T(p_T, l_2, E_{\tilde{t}}[p_T] - p_T) \tag{4.12}$$

where $\frac{\partial U_T}{\partial p_T} > 0$, $\frac{\partial U_T}{\partial l_2} > 0$, $\frac{\partial U_T}{\partial (E_{\tilde{t}}[p_T]) - p_T} < 0$. Thus, in addition to the positive marginal utilities of performance and leisure, we assume a negative marginal utility of worse than expected performance. Under this ex-post utility function and the same time constraint, the first order conditions modify to

$$\frac{\partial \mathcal{L}}{\partial e_2} = \frac{\partial U_T}{\partial p_T}\frac{\partial p_T}{\partial e_2} + \frac{\partial U_T}{\partial (E_{\tilde{t}}[p_T] - p_T)}\frac{\partial (E_{\tilde{t}}[p_T] - p_T)}{\partial e_2} + \lambda = 0 \tag{4.13}$$

$$\frac{\partial \mathcal{L}}{\partial l_2} = \frac{\partial U_T}{\partial l_2} + \lambda = 0 \tag{4.14}$$

which leads to the ex-post optimality condition

$$\frac{\partial U_T}{\partial p_T}\frac{\partial p_T}{\partial e_2} + \frac{\partial U_T}{\partial (E_{\tilde{t}}[p_T] - p_T)}\frac{\partial (E_{\tilde{t}}[p_T] - p_T)}{\partial e_2} = \frac{\partial U_T}{\partial l_2}. \tag{4.15}$$

At the end of the learning process, when their actual performance is known, biased indiviuals become aware of their initially biased self-assessment. The ex-post efficient optimum is therefore characterized by the optimality condition of an unbiased individual which reduces to

$$\frac{\partial U_T}{\partial p_T}\frac{\partial p_T}{\partial e_2} = \frac{\partial U_T}{\partial l_2}. \tag{4.16}$$

In the ex-post efficient optimum, the marginal utility of leisure equals the true marginal utility of effort. Ex post, an overconfident individual realizes that she underestimated the marginal utility of effort ex ante. Had she been aware of her overconfidence, she would have spent more effort. Therefore, the time allocation that was made under biased self-assessment yields less ex-post utility than the allocation that would have been made under unbiased self-assessment. In addition to the utility loss resulting from the inefficient time allocation, an overconfident individual loses even more utility due to the negative surprise resulting from the widened gap between expected and actual performance.

As shown above, $\frac{\partial p_T}{\partial \gamma} < 0$; hence, overconfidence widens the gap between expected and actual performance, $E_{\tilde{t}}[p_T] - p_T$, by lowering performance. This effect is reinforced by the fact that overconfidence not only lowers performance, but also inflates performance expectations. To see this, we derive the marginal impact of the overconfidence bias γ on expected performance[3]:

$$\frac{\partial E_{\tilde{t}}[p_T]}{\partial \gamma} = K_{\tilde{t}} + \left(\frac{\partial \Delta K^s_{\tilde{t}}}{\partial K^s_{\tilde{t}}} K_{\tilde{t}} + \frac{\partial \Delta K^s_{\tilde{t}}}{\partial e_2}\frac{\partial e_2}{\partial \gamma}\right) \tag{4.17}$$

$$= \left(1 + \frac{\partial \Delta K^s_{\tilde{t}}}{\partial K^s_{\tilde{t}}} + \frac{\partial \Delta K^s_{\tilde{t}}}{\partial e_2}\frac{\partial e_2}{\partial (1+\gamma) K_{\tilde{t}}}\right) K_{\tilde{t}} \tag{4.18}$$

The term in parentheses in (4.18) equals the change in expected performance with respect to a marginal increase in the current subjective knowledge level:

$$\frac{\partial E_{\tilde{t}}[p_T]}{\partial (1+\gamma) K_{\tilde{t}}} = 1 + \frac{\partial \Delta K^s_{\tilde{t}}}{\partial K^s_{\tilde{t}}} + \frac{\partial \Delta K^s_{\tilde{t}}}{\partial e_2}\frac{\partial e_2}{\partial (1+\gamma) K_{\tilde{t}}} > 0 \tag{4.19}$$

which we assume to be positive. We thus assume that an increase in subjective knowledge $K^s_{\tilde{t}}$ does not crowd out optimal effort so much that the optimal subjective knowledge in T, $E[p_T]$, decreases, i.e. $\frac{\partial \Delta K^s_{\tilde{t}}}{\partial K^s_{\tilde{t}}} > -1$. In other words, for identical utility and $\Delta K^s_{\tilde{t}}$ functions, a person who believes to know more in $t = \tilde{t}$ does also believe to know more in $t = T$. Under this assumption, (4.18) is clearly positive and the expectation-performance gap widens as a result of overconfidence.

In sum, overconfidence leads to inefficient time allocation. An overconfident individual invests less than optimal time in effort in the post-monitoring learning phase. As a consequence, overconfidence is associated with lower than optimal performance. At the same time, overconfidence inflates performance expectations. Both, the resulting expectation-performance gap and the inefficiently low performance decrease ex-post utility compared to an individual with unbiased self-monitoring.

For underconfidence, the effects on ex-post utility are ambiguous within this framework. On the one hand, the time allocation that was made ex ante turns out to be inefficient ex post as it does for overconfidence. Underconfident individuals spend inefficiently high effort and consume inefficiently low leisure. Again, the inefficiency of the chosen allocation decreases ex-post utility. On the other hand, and in contrast to overconfidence, underconfidence is associated with a positive surprise effect. The net effect of underconfidence on ex-post utility is therefore ambiguous. In the appendix, we show in an extended model with multiple tasks that underconfidence with regard to one task does not only lead to inefficiently low consumption of leisure, but also to

[3]The equality of (4.17) and (4.18) can be easily shown:

$$\frac{\partial E_{\tilde{t}}[p_T]}{\partial \gamma} = K_{\tilde{t}} + \left(\frac{\partial \Delta K^s_{\tilde{t}}}{\partial K^s_{\tilde{t}}} K_{\tilde{t}} + \frac{\partial \Delta K^s_{\tilde{t}}}{\partial e_2}\frac{\partial e_2}{\partial \gamma}\right) = \left(1 + \frac{\partial \Delta K^s_{\tilde{t}}}{\partial K^s_{\tilde{t}}}\right) K_{\tilde{t}} + \frac{\partial \Delta K^s_{\tilde{t}}}{\partial e_2}\frac{\partial e_2}{\partial \gamma} = \left(1 + \frac{\partial \Delta K^s_{\tilde{t}}}{\partial K^s_{\tilde{t}}}\right) K_{\tilde{t}} + \frac{\partial \Delta K^s_{\tilde{t}}}{\partial e_2}\frac{\partial e_2}{\partial \gamma}\frac{1}{K_{\tilde{t}}} K_{\tilde{t}}$$

$$= \left(1 + \frac{\partial \Delta K^s_{\tilde{t}}}{\partial K^s_{\tilde{t}}}\right) K_{\tilde{t}} + \frac{\partial \Delta K^s_{\tilde{t}}}{\partial e_2}\frac{\partial e_2}{\partial \gamma}\frac{1}{\frac{\partial (1+\gamma) K_{\tilde{t}}}{\partial \gamma}} K_{\tilde{t}} = \left(1 + \frac{\partial \Delta K^s_{\tilde{t}}}{\partial K^s_{\tilde{t}}} + \frac{\partial \Delta K^s_{\tilde{t}}}{\partial e_2}\frac{\partial e_2}{\partial \gamma}\frac{\partial \gamma}{\partial (1+\gamma) K_{\tilde{t}}}\right) K_{\tilde{t}}$$

$$= \left(1 + \frac{\partial \Delta K^s_{\tilde{t}}}{\partial K^s_{\tilde{t}}} + \frac{\partial \Delta K^s_{\tilde{t}}}{\partial e_2}\frac{\partial e_2}{\partial (1+\gamma) K_{\tilde{t}}}\right) K_{\tilde{t}}$$

inefficiently low spending of effort on other tasks. Thus, underconfidence comes at the cost of lower overall achievement, which, however, is not considered here.

Based on the model predictions, we put forward the following hypotheses to be tested empirically:

1. Overconfidence lowers actual performance (see (4.11)).
2. Overconfidence inflates expected performance (see (4.18)).
3. Low performance and worse than expected performance reduce ex-post utility (see (4.12)).

While our model explicitly considers the bias in assessing the existing knowledge level at $t = \tilde{t}$, it can easily be extended to integrate a bias in assessing effort productivity in the post-monitoring learning phase. The implications of this type of overconfidence would be the same. An individual who overestimates future knowledge gains would invest less than optimal time in effort, thus lowering her performance and inflating her performance expectations. As before, inefficiently low performance and the widened gap between actual and expected performance would decrease ex-post utility.

4.3 Setting and data

We empirically apply the model to a real world scenario. In the scenario under consideration, university students prepare for an exam which takes place at time $t = T$. At one point in time before the exam $t = \tilde{t}$, we make the existing knowledge level observable by conducting a multiple choice test on the exam-relevant topics and determining individual test scores. Additionally, at $t = \tilde{t}$ we ask students to estimate their existing knowledge level and inquire expectations about the future exam score and grade.

The main advantage of the selected scenario is that it perfectly mirrors the course of the learning process modeled in the theoretical framework. In particular, it allows us to objectively measure performance as well as existing exam-relevant knowledge. Another important feature is that participants have an inherent motivation to acquire and retrieve the tested fields of knowledge.

We visited ten tutorial groups to the lecture “Introduction to Economics” held at the University of Kiel in the winter term 2011/2012 in their penultimate session before the exam. In total, 108 students who took the regular exam two weeks later participated in the study. The questionnaire consisted of two parts. The first part contained ten multiple choice questions on various topics taught within the course. Three answer options were provided for each question among which only one option was correct. The style of the questions was comparable to the multiple choice section of the final exam. The second part then inquired about a student’s self-evaluation of her own performance in the previous multiple choice test and about her expectations for the future exam. Specifically, students were asked to estimate the number of correct answers in the multiplce choice test (0-10) as well as the score and grade they would obtain in the final exam. Possible exam scores ranged from 0 to 120 and were transformed into grades from 0 (failed) to 10 (excellent) in steps of one. In addition, the second part collected information on each student’s sex, field of study and final high school grade (“Abiturnote”). The second part of the questionnaire was distributed after the first part had been completed and collected. Completing the whole questionnaire took about 15 to 20 minutes (8-13 minutes for the first part plus 5-7 minutes for the second part). After exam results were published, we elicited students’ individual happiness with their result on a scale from very unhappy (1) to very happy (10) by email.

We operationalize the concept of overconfidence by comparing the score an individual i estimates she has achieved in the multiple choice test, mc_i^s, and the score she actually achieved, mc_i. The actual score is intended to reflect the knowledge level at $t = \tilde{t}$ whereas the estimated score represents its subjective counterpart.

Consistent with the theoretical formulation in (4.3), we define overconfidence as the relative overestimation of the true score:

$$overconfidence_i = (mc_i^s / mc_i) - 1. \tag{4.20}$$

The more the estimated score exceeds the actual score, the more pronounced is overconfidence. Negative overconfidence implies underconfidence with regard to current knowledge.

To address concerns that observed biases may not reflect genuinely biased beliefs, but result from insufficient mental effort or a motivation to self-enhance, we monetarily incentivize accuracy of estimates in a treatment group. Monetary incentives have been shown to reduce self-presentational concerns and increase effort to answer questions correctly (Camerer and Hogarth, 1999). Thus, providing incentives for accurate estimates should reduce the controllable part of observed overconfidence and yield insights into the incidence of its behaviorally relevant part (Ehrlinger et al., 2008).

Subjects in the treatment group earned five Euros for each correct performance estimate (multiple choice test score, exam score (± 3) and exam grade). The maximum payout in the treatment group amounted to fifteen Euros. Average payout was 4.10 Euros. To prevent strategic behavior by leaving questions in the multiple choice test unanswered, participants were not informed about the content of the second part of the questionnaire before they had completed the first part. The control group received a flat payment of five Euros for full completion of the questionnaire. Relative to the time it took to complete the questionnaire, the financial compensation was highly rewarding. Only five participants refused to stay for the survey, mostly because they had appointments right after the tutorial session.

To test whether monetary incentives can reduce observed biases, we regress observed biases and their absolute values on a monetary treatment dummy. As shown in Table C.3 in the appendix, monetary incentives are not significantly related to the accuracy of performance estimates or observed overconfidence. It therefore seems that subjects were truly unable to correctly postdict their test score. This result is in line with the few other studies considering incentives and overconfidence (Hacker et al., 2008, Yates et al., 1997, Hoelzl and Rustichini, 2005, Ehrlinger et al., 2008, and Clark and Friesen, 2009). It seems that the quality of monitoring is largely not controllable by the learner. This result speaks in favor of a cognitive rather than a motivational explanation for overconfidence. Therefore, a relationship between observed overconfidence and the functioning of cognitive processes is likely.

Other important variables in the theoretical model are performance, performance expectations and ability. We measure performance by the percentage score individual i obtains in the exam, i.e. $performance_i = (exam_i/120) \times 100$. Correspondingly, the expected performance is defined as the percentage exam score that individual i expects to obtain in the exam, i.e. $E[performance]_i = (exam_i^s/120) \times 100$. As a proxy for cognitive ability, we refer to the *high school grade*. The high school grade is a weighted average of grades obtained during the last two years in high school and ranges from failed (0) to excellent (10). School achievement has been shown to be closely linked to general mental ability. Correlations between measures of school achievement and general mental ability are typically around .5 which makes general mental ability the best known predictor of school success (Gustafsson and Undheim, 1996, Spinath et al., 2006).

Finally, *happiness* or satisfaction with the obtained grade is defined on a ten point scale ranging from very unhappy (1) to very happy (10). When estimating the impact of performance and the expectation-performance gap on happiness, we consider grades instead of raw scores because they are more relevant to the student than the underlying scores. Actually obtained and expected grades range from failed (0) to excellent (10). The expectation-performance gap is calculated as the difference between the expected and the actual grade.

4.4 Empirical analysis

4.4.1 Descriptive analysis

Subjects are fairly inaccurate in estimating their performance in the multiple choice test. Estimates deviate from the true values by an average of 35%. The bias is upward with an average overestimation of 22%. Thus, the sample as a whole is characterized by overconfidence. Both the overconfidence bias as well as as its absolute value are significantly different from zero. Hidden in these aggregate figures is considerable heterogeneity between subjects. Slightly more than 50% of the sample is overconfident. About 20% correctly estimate their score. And a non-negligible share of 30% is underconfident.

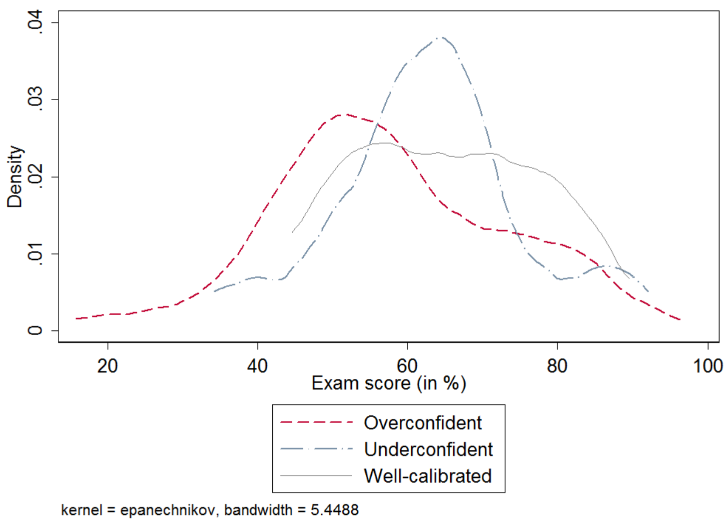
We now consider the univariate relationship between overconfidence, and performance and expected performance in the final exam. Figure 4.3 provides the kernel density estimates of the (expected) exam performance for over-, under- and normal-confident students. Consistent with our hypothesis, these unconditional plots suggest that overconfident students perform worse than underconfident students. On average, overconfident students achieved about 57% of the maximum score whereas the score distribution of the underconfident is shifted to the right with an average score of about 63%. In contrast, overconfident students expect an average of 73% of the maximum score whereas the underconfident only expect about 70%.

The scatter plots in Figure 4.4 confirm the impression of a negative correlation between overconfidence and performance and a slight positive correlation between overconfidence and expectations. The graphs clearly show that increasing confidence during the learning stage is associated with poorer performance and higher performance expectations.

Finally, the scatter plots in Figure 4.5 visualize the relationship between performance, the expectation-performance gap and happiness. The upper panel shows that better grades are associated with higher levels of happiness. The lower panel shows that pleasant surprises, i.e. negative expectation-performance gaps, are associated with higher happiness levels than unpleasant surprises.

Figure 4.3: Kernel densities by type of bias

(a) Exam score



(b) Expected exam score

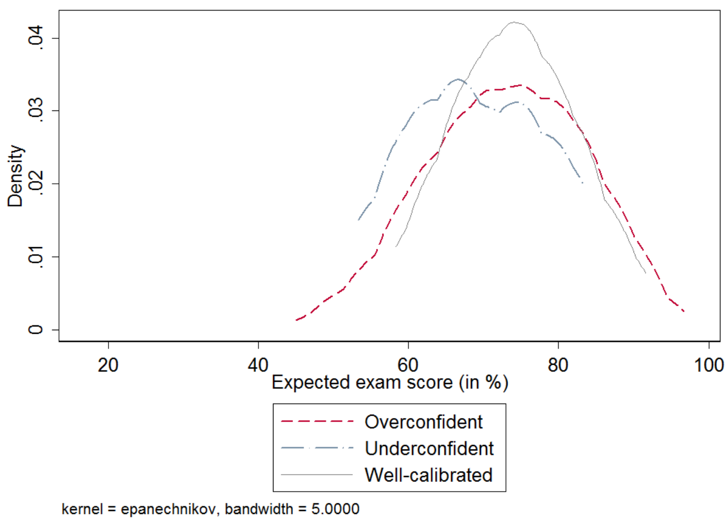
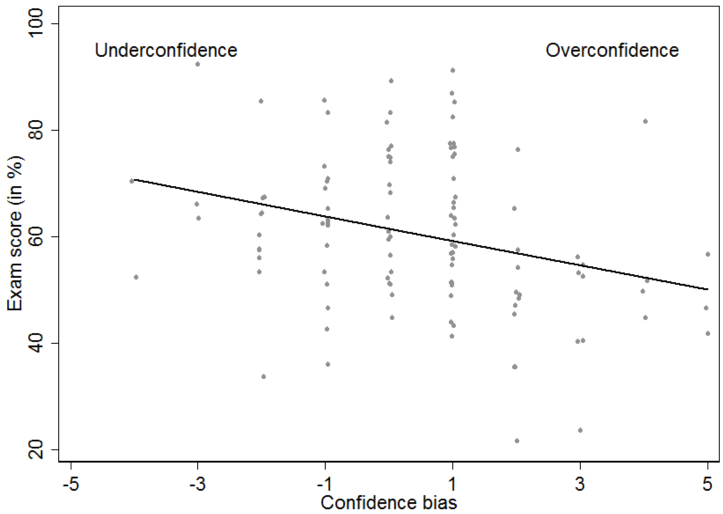


Figure 4.4: Overconfidence bias and (expected) percentage exam score, linear fit

(a) Exam score



(b) Expected exam score

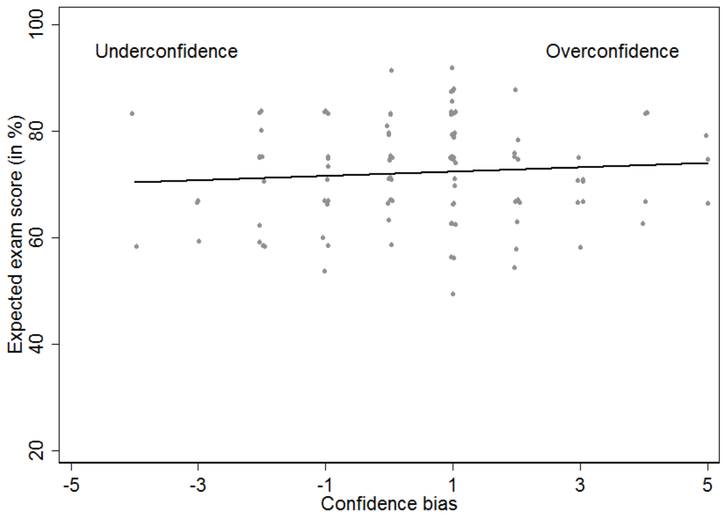
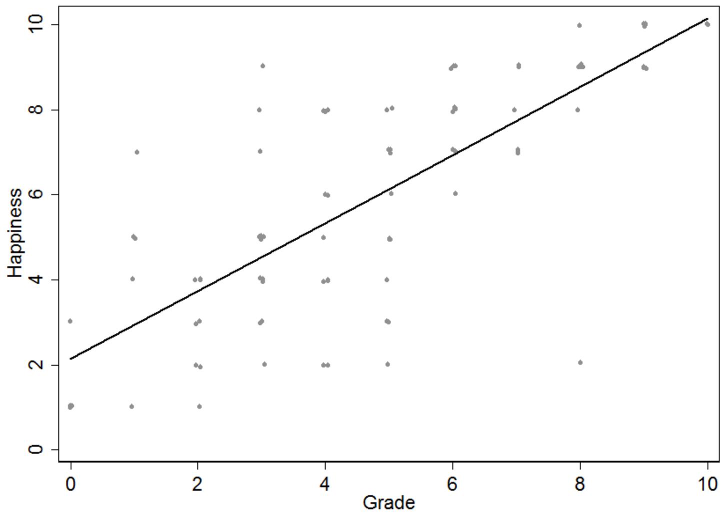
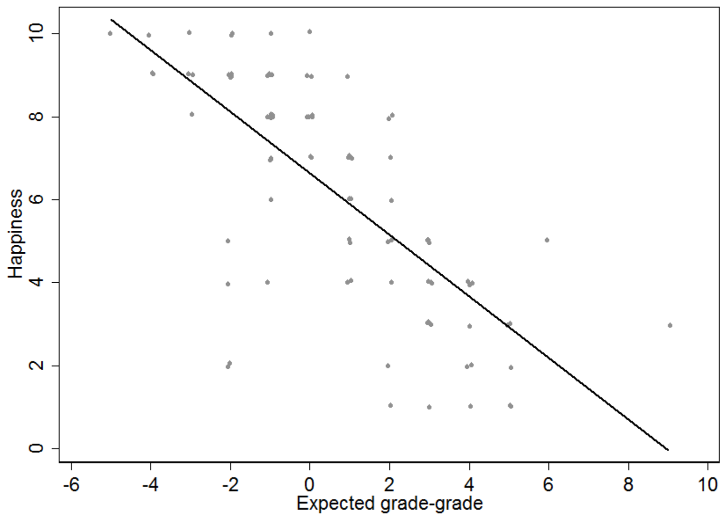


Figure 4.5: Performance, expectations, happiness

(a) Grade



(b) Expected grade-grade



4.4.2 Econometric analysis

The descriptive analysis offers support for the predictions of the theoretical model. To control for potentially important dimensions of heterogeneity between individuals, however, we also conduct an econometric analysis of the relationship between overconfidence, (expected) performance and happiness.

Overconfidence and performance

We first test the hypothesis that overconfidence lowers performance. Using ordinary least squares, we regress performance as measured by the percentage score obtained in the exam on overconfidence:

$$performance_i = \alpha + \beta\, overconfidence_i + X_i'\,\delta + u_i$$

where $overconfidence_i$ is the degree of overconfidence of individual i, X_i a vector of control variables and u_i an error term. If overconfidence lowers performance, we expect β to be negative.

Table 4.1 summarizes the results. In column 1, we start with the most parsimonious specification. Following the theoretical model, exam performance is a function of ability as proxied by high school grade, and of the degree of overconfidence as the prime determinant of effort spent on learning. We find clear support for the hypothesis that overconfidence lowers performance. A ten percentage point increase in the degree of overconfidence is associated with a 0.73 percentage point reduction in the exam score. Accordingly, a standard deviation increase in the degree of overconfidence (0.57) is associated with a more than four percentage point reduction in the exam score. As expected, individuals with better high school grades also perform better in the exam.

We check the robustness of this result by gradually expanding the set of control variables. Column 2 adds a dummy variable indicating whether an individual was provided monetary incentives to estimate her performance in the multiple choice test more accurately. The coefficient of overconfidence, however, remains the same. This result is in line with the previous finding that monetary incentives did not make an individual more accurate in estimating her performance in the multiple choice test (Table C.3 in the appendix).

Column 3 considers the possibility that overconfident individuals may have different aspiration levels and additionally controls for the exam grade at which an individual would have been satisfied with her performance. While higher aspirations go along with higher exam scores, they do not affect the estimated relationship between overconfidence and performance.

Column 4 controls for individual heterogeneity in terms of field of study (economics versus other fields of studies) and sex (male versus female). It also adds a full set of tutor dummies to take into account that the tutorials accompanying the lecture were held by four different tutors. None of these variables is significantly related with exam performance and the coefficient of overconfidence is fully robust to their inclusion.

Overall, the results presented in Table 4.1 strongly support the hypothesis that overconfidence lowers performance. While we cannot exclude the possibility that our results are driven by unobserved heterogeneity, the stability of the coefficient of overconfidence across the different specifications suggests little role for an unobserved confounder. To fully explain away the estimated relationship between overconfidence and performance, an unobserved confounder must be much more strongly associated with overconfidence and performance than our set of control variables which already capture many important dimensions of heterogeneity.

Table 4.1: Regression results for the exam performance

	Model 1	Model 2	Model 3	Model 4
Overconfidence	-7.3***	-7.3***	-6.9***	-6.2***
	(1.9)	(1.9)	(1.8)	(1.9)
High school grade	3.2***	3.2***	3.0***	3.0***
	(0.7)	(0.7)	(0.7)	(0.7)
Monetary incentives		1.0	1.4	
		(2.4)	(2.3)	
Satisfactory grade			1.9***	1.9***
			(0.6)	(0.7)
Economics student				-3.6
				(2.8)
Male				3.6
				(2.5)
Tutor 2				-1.3
				(3.6)
Tutor 3				1.2
				(3.5)
Tutor 4				-3.4
				(3.2)
Constant	43.2***	43***	33.5***	33.9***
	(4.4)	(4.4)	(5.7)	(6.4)
R squared	0.27	0.27	0.33	0.36
N	108	108	108	108

Results of OLS estimation. Dependent variable is the percentage exam score. ***/**/* denote significance at a 1/5/10 per cent level. Robust standard errors in parentheses.

Overconfidence and performance expectations

We next test the hypothesis that overconfidence inflates expected performance by regressing expected performance as measured by the expected percentage score obtained in the exam on overconfidence:

$$E[performance]_i = \phi + \lambda\, overconfidence_i + Y_i'\, \mu + v_i$$

where Y_i is a vector of control variables and v_i an error term. If overconfidence inflates expected performance, we expect λ to be positive.

Table 4.2 summarizes the results. Again, column 1 starts with a parsimonious specification that closely builds on the theoretical model. In addition to ability, we also include an individual's existing knowledge level at the time the multiple choice test was conducted and expectations were made (see (4.2)). We control for an individual's actual knowledge level rather than her subjective knowledge level, so that the variable does not capture the effects of overconfidence. We find strong support for the hypothesis that overconfidence increases expected performance. A ten percentage point increase in the degree of overconfidence is associated with a 0.64 percentage point increase in the expected exam score. Or, a standard deviation increase in the degree of overconfidence (0.57) is associated with an increase in the expected exam score by almost four percentage points. The estimated relationship between overconfidence and expected performance is robust to adding controls for monetary incentives (column 2) and field of study, sex and tutor (column 3).

Table 4.2: Regression results for the expected exam performance

	Model 1	Model 2	Model 3
Overconfidence	6.4***	6.0***	5.0**
	(1.9)	(1.9)	(1.9)
High school grade	0.6	0.5	1.0*
	(0.5)	(0.5)	(0.6)
MC score	2.6***	2.5***	2.2***
	(0.6)	(0.7)	(0.6)
Monetary incentives		2.6	
		(1.6)	
Economics student			3.2*
			(1.7)
Male			1.8
			(1.8)
Tutor 2			-3.8*
			(2.2)
Tutor 3			-1.0
			(2.8)
Tutor 4			-4.3**
			(2.1)
Constant	52.0***	52.1***	51.6***
	(4.4)	(4.4)	(5.0)
R squared	0.16	0.18	0.23
N	108	108	108

Results of OLS estimation. Dependent variable is the expected percentage exam score. ***/**/* denote significance at a 1/5/10 per cent level. Robust standard errors in parentheses.

Performance, expectations and happiness

We have shown that overconfidence is strongly associated with lower levels of actual performance and inflated levels of expected performance. As argued above, overconfidence should therefore affect subjective well-being. We test the resulting hypothesis that lower performance and a larger expectation-performance gap reduce grade happiness or satisfaction with the obtained grade. The empirical specification takes the following form:

$$happiness_i = \rho + \sigma\, grade_i + \tau\, (E[grade] - grade)_i + Z_i'\, \theta + w_i$$

where Z_i is a vector of control variables and w_i an error term. If lower grades and larger expectation-performance gaps reduce happiness, we expect σ to be positive and τ to be negative.

As column 1 in Table 4.3 shows, this is indeed the case. Lower grades are associated with significantly lower levels of happiness than higher grades. And bad surprises in the form of worse than expected grades are negatively related with the level of happiness, too. We also assess the direct relationship between overconfidence and happiness. If overconfidence lowers actual performance and increases expected performance and both in turn reduce happiness, overconfidence should also be directly associated with lower levels of happiness. Indeed, as column 2 shows, overconfidence is significantly and negatively associated with happiness.

The estimated coefficients of the main specification in column 1 do not change after controlling for high school grade, field of study, sex and tutor (column 3). One may be concerned that a considerable number of students did not respond to the email in which we inquired about a student's satisfaction with the grade (the number of observations drops to 89). If students who did not respond were particularly unhappy with the grade, possibly as a result of overconfidence, systematic non-response may bias the coefficients of interest. To address this potential attrition bias, we employ the method of inverse probability weights. We predict the probability of responding to our email by individual characteristics using a probit model for the complete sample of students. These characteristics include the high school grade, the field of study, sex, and tutor as well as the exam grade and the difference between the actual and expected grade. As argued above, both the grade and the difference between the actual and the expected grade are prime determinants of grade satisfaction. They should therefore play an important role in explaining response to our email. We then compute the inverse probability of responding to our email for each student and use it as a weight for the respective observation in our sub-sample of students who did respond to our happiness question by email. Hence, students with a low estimated probability of response are attached a higher weight and vice versa. As column 4 shows, the use of inverse probability weights does not affect the estimated relationship between happiness, performance and the expectation-performance gap. We are therefore confident that attrition bias does not constitute a major problem in our analysis.

Table 4.3: Regression results for the happiness level

	Model 1	Model 2	Model 3	Model 4
Grade	0.5***		0.6***	0.5***
	(0.1)		(0.1)	(0.1)
Estimated grade-grade	-0.3**		-0.4**	-0.4***
	(0.1)		(0.1)	(0.1)
Overconfidence		-0.9*		
		(0.5)		
High school grade			0.0	0.0
			(0.1)	(0.1)
Economics student			0.4	0.5
			(0.4)	(0.4)
Male			-0.2	-0.3
			(0.4)	(0.4)
Tutor 2			-0.3	-0.3
			(0.6)	(0.6)
Tutor 3			0.1	0.1
			(0.5)	(0.5)
Tutor 4			0.4	0.5
			(0.5)	(0.5)
Constant	3.6***	6.2***	3.5***	3.7***
	(0.8)	(0.3)	(0.9)	(0.9)
R squared	0.6	0	0.6	0.7
N	89	90	86	86

Results of OLS estimation. Dependent variable is the happiness level ranging from 1 (very unhappy) to 10 (very happy). ***/**/* denote significance at a 1/5/10 per cent level. Robust standard errors in parentheses. In model 4, inverse probability weights are used.

4.5 Conclusion

This paper studies the costs of overconfidence during preparation for a future task. We show theoretically and empirically that overly optimistic beliefs about one's own existing knowledge are detrimental for future objective task performance and subjective well-being.

In accordance with metacognitive theory and models of self-regulated learning, we attribute the performance-reducing effect of overconfidence to insufficient effort spending. Thus, providing regular feedback may help individuals who think they know more than they actually do to allocate their time more efficiently. It may also help them to form more realistic performance expectations and avoid disappointment and frustration. Ultimately, seeing oneself more often in an unbiased mirror may allow overconfident individuals to obtain better objective and subjective outcomes.

It is important to note that our results apply to a single task and do not necessarily generalize to overall achievement across different tasks. Obviously, if an individual spends all her time on one particular task due to her underconfidence with regard to this task, she might perform extraordinarily well in that task, but achieve nothing else. Accordingly, underconfident individuals may forgo important opportunities in life. The university students in our sample are a case in point. The sampled individuals have all been sufficiently confident to enrol in a university, select the introductory economics course and take the exam. By contrast, highly underconfident individuals may have opted against trying to obtain a university degree even if they had the intellectual ability to do so.

Therefore, making conclusions about the costs and benefits of overconfidence requires a broader view. We share the view of Kahneman, 2011, that goals which people set for themselves influence where they end up and how they feel about it. On the one hand, setting ambitious goals pushes individuals towards coming close to them. On the other hand, setting goals that are (too) difficult to achieve fuels dissatisfaction. Similar to goal setting, finding the right balance between confidence and scepticism about oneself seems promising for a successful and satisfying life.

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Chapter 5

Overconfidence and Risk Taking of Ethiopian Farmers[1]

5.1 Introduction

Fluctuating yields and prices of agricultural products make agricultural income highly volatile. Managing this volatility is particularly challenging for farmers in developing countries where access to formal credit and insurance markets is limited. Therefore many poor farm households need to rely on inefficient strategies to manage risk ex ante and cope with shocks ex post (Fafchamps, 1992, Morduch, 1995, Townsend, 1995, Dercon, 2002, Kurosaki and Fafchamps, 2002).

An important strategy for managing risk ex ante is the careful selection of income generating activities. Farm households typically face a tradeoff between the riskiness of an activity and its expected return and may hence be forced to forego higher mean returns in exchange for low risk. In addition, they need to consider that returns to different income generating activities may be correlated. In order to keep overall risk low, farm households therefore tend to engage in low-risk, low-return activities and diversify their income generating activities, which prevents them from realizing gains from specialization (Rosenzweig and Binswanger, 1993, Dercon, 1996).

If shocks occur despite ex ante risk management, households use various ex post coping strategies. Examples include receiving support from relatives and friends, selling financial and non-financial assets or increasing labor supply including child labor. These strategies may be effective in case of idiosyncratic shocks like illness or job loss. In the event of covariate shocks like drought which simultaneously affect the whole environment, however, their effectiveness is limited. In addition, coping strategies like selling productive assets and taking children out of school reduce the future income generating capacity of a household and may increase its vulnerability to future shocks.

[1]This chapter is a slightly modified version of the working paper "Overconfidence and Risk Taking of Ethiopian Farmers" jointly written with Toman Omar Mahmoud and Ulrich Schmidt.

In sum, both ex ante risk management and ex post coping strategies pose a costly task to farm households in developing countries. Traditionally, the volatility of agricultural income has been attributed to external factors such as rainfall variability, the eventual arrival of crop disease or pest infestation. Arguably, these factors are often beyond farmer's control. In this paper, we propose that part of the observed volatility in agricultural income may not result from external factors but from overconfidence, a psychological bias of the individual farmer.

Overconfidence is a robust phenomenon in the psychology of judgment which has received increasing attention in the behavioral economics literature (see Odean, 1998, Klayman et al., 1999, and Glaser et al., 2004, for a broad overview over the relevant literature). The literature distinguishes between three types of overconfidence. The first type of overconfidence is unrealistically positive self-evaluation. It describes the tendency to overestimate one's own positive attributes in absolute terms or relative to others (Greenwald, 1980). The second type of overconfidence is unrealistic optimism or illusion of control. It refers to a systematic overestimation of personal success probabilities (Langer, 1975). The third type of overconfidence is miscalibration. It denotes a systematic overestimation of the precision of one's knowledge which implies an underestimation of the variance of random variables (Lichtenstein et al., 1982).

Numerous studies provide evidence for the presence of all types of overconfidence in a wide range of populations. A famous example is the study by Svenson, 1981, who asked students to assess their own driving skills. 82% of the respondents judged themselves to be in the top 30% of the group. Other examples include overestimated management skills (Malmendier and Tate, 2005, 2008), the overestimated ability to interpret information, the overestimated precision of available information (Odean, 1998, 1999) and underestimated probabilities of future adverse events such as health hazards (Weinstein, 1980). However, only few studies assess the degree of overconfidence among farmers which are furthermore limited to developed countries, see e.g. Eales et al., 1990, Pease et al., 1993, Buzby et al., 1994, Sherrick, 2002. These studies suggest that the phenomenon of overconfidence is also common among farmers.

Several theoretical and empirical studies analyze the impact of overconfidence on decision making. Most of these studies come from the behavioral finance literature and focus on the role of overconfidence for investment decisions and financial market outcomes. In this literature, overconfidence is usually modeled as miscalibration. If subjects underestimate the volatility of financial assets, riskier portfolios become more attractive (Odean, 1999). The impact of unrealistically positive self-evaluation and unrealistic optimism on portfolio choice has not yet been studied theoretically although some empirical studies suggest that these types of overconfidence may have a strong impact on investment behavior (Biais et al., 2005, Glaser and Weber, 2007).

We add to this literature by showing with a simple theoretical model that unrealistically positive self-evaluation and unrealistic optimism lead, as miscalibration, to riskier portfolios. In addition, we empirically assess the presence of these types of overconfidence and their behavioral implications in a new setting. Instead of analyzing the impact of financial investors' overconfidence on asset portfolios, we consider the impact of overconfidence of poor small-holder farmers in a developing country on their crop cultivation portfolios. This setting is particularly interesting for several reasons. The crop cultivation decision represents an everyday decision of about 500 million small-holder farmers. These farmers represent the overwhelming majority of people living in rural areas of the developing world. Small-holder farmers have to directly bear the consequences of their decision making. These may even affect the survival of the household as small-holder farmers rely on current farm output to meet their subsistence needs. This is in contrast to financial investors who are typically paid high fix salaries and may solely lose their bonuses.

Our key hypothesis is that a farmer who overestimates his ability to generate crop yields or underestimates the probability of future shocks is inclined to take excessively high risk in crop cultivation activities. His biased behavior causes a partial failure of ex ante risk management and thus higher than optimal volatility of crop returns. The associated welfare loss results from an inefficiently frequent use of ex post coping strategies, caused by the excessive income volatility.

We test the hypothesis that overconfidence increases risk taking by studying the relationship between overconfidence and the riskiness of crop cultivation choices in a sample of small-holder farmers in rural Ethiopia. We classify a farmer as overconfident in the sense of unrealistically positive self-evaluation if he believes to be more productive relative to other farmers in the same community than he actually is. Overconfidence in the sense of unrealistic optimism is measured by an index that aggregates individual subjective probabilities of future covariate agricultural shocks. As we only consider covariate shocks, they should affect all community members with the same probability. Thus, differences in stated probabilities reflect differences in individual optimism about not being adversely affected in the future.

Individual risk taking is measured as the average standard deviation of returns per hectare that is associated with the crop cultivation portfolio chosen by the individual farmer, where a portfolio is characterized by the area that is allocated to different crops. For each individual portfolio, we thus calculate by how much returns would have fluctuated in the past assuming average regional yields and prices. The more average returns would have fluctuated, the riskier the crop cultivation portfolio.

In line with our hypothesis, we find that overconfident farmers cultivate riskier crops. Our finding implies that overconfidence increases the volatility of agricultural income. Part of the observed volatility of agricultural income may therefore not be the result of adverse covariate shocks such as fluctuations in rainfall, but of individual psychological traits of farmers who overestimate their skills and abilities or underestimate shock probabilities. Human deficiency may thus amplify the already substantial income volatility caused by unstable weather conditions. As a consequence farm households in developing countries need to more frequently apply inefficient coping strategies which reduces their welfare.

5.2 Overconfidence and the risk-return tradeoff

Individuals frequently face a tradeoff between the mean return to an activity and its riskiness. We argue that overconfidence in the form of unrealistically positive self-evaluation and unrealistic optimism wrongly inflates the expected returns to a risky activity. In expectation of high returns, overconfident individuals take inefficiently high risk and end up with undesired levels of return volatility.

We study farmers in a developing country who determine their accepted level of riskiness in crop cultivation by allocating their cultivable land to different crops. The decision situation of a farmer can be described with the following simple theoretical model. A farmer with land holdings of x hectare decides on the cultivation of two different crops, crop s and crop r. Crop s is a low-risk, low-return crop. For simplicity and without loss of generality, we assume that it is a safe crop that always generates returns of p_s per hectare. Crop r is a high-risk, high-return crop that is exposed to covariate shocks comprising yield and price shocks occuring with probability π. Returns to crop r are hence state specific. If no shocks occur, its return amounts to $p_r > p_s$ per hectare. If a shock occurs, its return equals zero.

We first consider the case of a farmer who evaluates himself unrealistically positive. We assume that unrealistically positive self-evaluation implies an overestimation of the returns of cultivating the risky crop by an amount $\delta > 0$ in both states. We assume that overconfidence does not affect the expected returns from cultivating the safe crop. This assumption seems plausible, as no sensible farmer should form erroneous expectations regarding a certain outcome.

Let α denote the share of land holdings the farmer allocates to the risky crop. Then, the subjectively estimated return of a crop portfolio equals $(\alpha(p_r + \delta) + (1 - \alpha)p_s)x$ if no shock occurs and $(\alpha\delta + (1 - \alpha)p_s)x$ if a shock occurs. Obviously, it is profitable to cultivate both crops only if $p_r + \delta$ and p_s are positive. Moreover, we assume that the subjectively expected return of the risky crop exceeds the return of the safe crop $((1 - \pi)(p_r + \delta) + \pi\delta > p_s)$ since otherwise no risk averse farmer would cultivate the risky crop. We further assume that farmers exhibit constant relative risk aversion.[2] When determining the optimal value of α, a farmer maximizes his expected utility

$$EU = (1 - \pi)((\alpha(p_r + \delta) + (1 - \alpha)p_s)x)^\beta + \pi((\alpha\delta + (1 - \alpha)p_s)x)^\beta$$

where β is the coefficient of relative risk aversion. For a risk averse farmer $\beta < 1$[3].

[2] Assuming constant relative risk aversion is standard practice in theoretical and empirical studies of portfolio choice. Recently, the validity of the assumption of constant relative risk aversion has been directly tested. Using longitudinal data Brunnermeier and Nagel, 2008, and Chiappori and Paiella, 2011 have shown that changes in the level of wealth do not significantly affect the portfolio composition, which indicates that relative risk aversion is indeed constant.

[3] For convenience, we assume that $\beta > 0$ in the theoretical analysis such that the utility function is given by $u(x) = x^\beta$. In general $u(x) = lnx$ for $\beta = 0$ and $u(x) = -x^\beta$ for $\beta < 0$. It is straightforward to show that our results also hold for nonpositive values of β. We consider the case of risk averse

Proposition 1

For a risk averse farmer the optimal share of land allocated to the risky crop α increases with the overestimation δ of the returns to the risky crop.

Proof of proposition 1

The first-order condition for deriving the optimal value of α is given by

$$\frac{dEU}{d\alpha} = (1-\pi)\beta((\alpha(p_r+\delta)+(1-\alpha)p_s)x)^{\beta-1}(p_r+\delta-p_s)x+\pi\beta((\alpha\delta+(1-\alpha)p_s)x)^{\beta-1}(\delta-p_s)x = 0,$$

which yields

$$((1-\pi)(p_r+\delta-p_s))^{\frac{1}{\beta-1}}(\alpha(p_r+\delta)+(1-\alpha)p_s) = (\pi(p_s-\delta))^{\frac{1}{\beta-1}}(\alpha\delta+(1-\alpha)p_s).$$

Defining $A = ((1-\pi)(p_r+\delta-p_s))^{\frac{1}{\beta-1}}$ and $B = (\pi(p_s-\delta))^{\frac{1}{\beta-1}}$, the optimal value of α is given by

$$\alpha = \frac{(B-A)p_s}{(B-A)p_s + A(p_r+\delta) - B\delta}$$

which yields

$$\frac{1}{\alpha} = 1 + \frac{A(p_r+\delta)-B\delta}{(B-A)p_s}.$$

Obviously, α is increasing in δ iff $1/\alpha$ is decreasing in δ. We get

$$\frac{d\frac{1}{\alpha}}{d\delta} = \frac{(\frac{dA}{d\delta}(p_r+\delta)+A-\frac{dB}{d\delta}\delta-B)(B-A)p_s-(\frac{dB}{d\delta}-\frac{dA}{d\delta})p_s(A(p_r+\delta)-B\delta)}{(B-A)^2p_s^2}$$

and have to show that the numerator is negative. The numerator can be simplified to $-(B-A)^2p_s + p_sp_r((dA/d\delta)B - (dB/d\delta)A)$ and is negative if $(dB/d\delta)A > (dA/d\delta)B$. We get

$$\frac{dA}{d\delta}B = \frac{1}{\beta-1}((1-\pi)(p_r+\delta-p_s))^{\frac{1}{\beta-1}-1}(1-\pi)(\pi(p_s-\delta))^{\frac{1}{\beta-1}} < 0$$

and

$$\frac{dB}{d\delta}A = \frac{1}{\beta-1}(\pi(p_s-\delta))^{\frac{1}{\beta-1}-1}(-\pi)((1-\pi)(p_r+\delta-p_s))^{\frac{1}{\beta-1}} > 0$$

which completes the proof. Thus, a farmer who evaluates himself unrealistically pos-

farmers as many empirical studies have shown that decision makers are generally risk averse (see e.g. Harrison et al., 2005 and Harrison et al., 2007).

itive and overestimates the returns to the risky crop takes more risk in the optimal allocation.[4]

Similarly, we can show within this simple framework that not only unrealistically positive self-evaluation but also unrealistic optimism leads to increased risk taking. We assume that an unrealistically optimistic farmer underestimates his personal risk of return shocks by ϵ such that the subjective probability of a shock amounts to $\pi - \epsilon > 0$. Expected utility is then given by

$$EU = (1-\pi+\epsilon)((\alpha p_r + (1-\alpha)p_s)x)^\beta + (\pi-\epsilon)((1-\alpha)p_s x)^\beta.$$

Proposition 2

For a risk averse farmer the optimal share of land allocated to the risky crop α increases with the underestimation ϵ of the shock probability.

Proof of proposition 2

The first order condition is now given by

$$\frac{dEU}{\alpha} = \beta(1-\pi+\epsilon)((\alpha p_r+(1-\alpha)p_s)x)^{\beta-1}(p_r-p_s)x+\beta(\pi-\epsilon)((1-\alpha)p_s x)^{\beta-1}(-p_s x) = 0,$$

which yields

$$((1-\pi+\epsilon)(p_r-p_s))^{\frac{1}{\beta-1}}(\alpha p_r + (1-\alpha)p_s) = ((\pi-\epsilon)p_s)^{\frac{1}{\beta-1}}(1-\alpha)p_s.$$

Defining $C = ((1-\pi+\epsilon)(p_r-p_s))^{\frac{1}{\beta-1}}$ and $D = ((\pi-\epsilon)p_s)^{\frac{1}{\beta-1}}$, the optimal value of α is now given by

$$\alpha = \frac{(D-C)p_s}{(D-C)p_s + Cp_r}$$

which yields

$$\frac{1}{\alpha} = 1 + \frac{Cp_r}{(D-C)p_s}$$

and

$$\frac{d\frac{1}{\alpha}}{d\epsilon} = \frac{\frac{dC}{d\epsilon}p_s p_r(D-C) - (\frac{dD}{d\epsilon} - \frac{dC}{d\epsilon})p_s p_r C}{(D-C)^2 p_s^2}$$

and again we have to show that the numerator is negative such that $1/\alpha$ is decreasing

[4] So far we have assumed symmetric overestimation of returns of the risky crop in both states by the amount δ. Alternatively, one could also assume asymmetric overestimation where the farmer would overestimate returns only in the good state (no shock occurs) or only in the bad state (a shock occurs). The theoretical prediction of increased risk taking as a result of overconfidence also holds for these asymmetric cases. Proofs are available upon request.

in ϵ. The numerator can be simplified to $p_s p_r((dC/d\epsilon)D - (dD/d\epsilon)C)$ and is negative if $(dC/d\epsilon)D < (dD/d\epsilon)C$. We get

$$\frac{dD}{d\epsilon}C = \frac{1}{\beta-1}((\pi-\epsilon)p_s)^{\frac{1}{\beta-1}-1}(-p_s)((1-\pi+\epsilon)(p_r-p_s))^{\frac{1}{\beta-1}} > 0$$

$$\frac{dC}{d\epsilon}D = \frac{1}{\beta-1}((1-\pi+\epsilon)(p_r-p_s))^{\frac{1}{\beta-1}-1}(p_r-p_s)((\pi-\epsilon)p_s)^{\frac{1}{\beta-1}} < 0$$

which completes the proof.

In sum, we have shown that overconfidence increases the share of land allocated to the risky crop. Overconfidence thus leads to an inefficiently risky composition of the crop cultivation portfolio. The inefficiency of the chosen portfolio clearly reduces the welfare of the farmer. The farmer would have chosen a less risky portfolio had he been aware of his overconfidence even though the riskier portfolio generates higher average returns.

Based on the model predictions, we put forward the following hypotheses:

1. Unrealistically positive self-evaluation increases risk taking through the composition of the crop cultivation portfolio.

2. Unrealistic optimism increases risk taking through the composition of the crop cultivation portfolio.

5.3 Setting and data

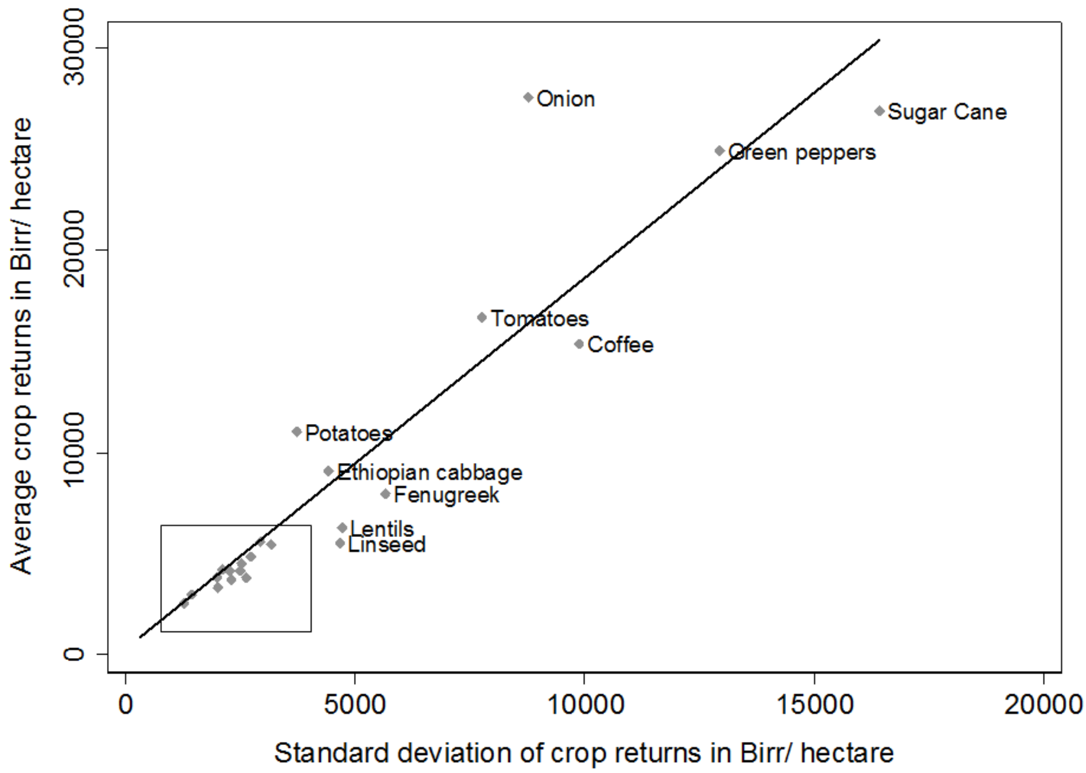
We test these hypotheses using data from small-holder farmers from rural Ethiopia. This particular setting has several advantages. First, farmers in Ethiopia face a clear risk-return tradeoff in crop cultivation. The most common crop is teff, a grass indigenous to Ethiopia. Teff furnishes injera, Ethiopia's national dish which is eaten daily in most households throughout the country. Other common crops are wheat, barley, chickpeas and maize. These crops promise relatively low, but stable returns. Higher returns are associated with the cultivation of onion, tomatoes, potatoes and other vegetables, which, however, fluctuate much more severely. As shown in Figure 5.1, means and standard deviations of common crop returns vary widely and are highly correlated. There is a clear tradeoff between returns to a crop and the risk involved.

Second, agricultural income in Ethiopia is highly volatile due to frequent covariate shocks. Agriculture in Ethiopia is particularly vulnerable to rainfall shocks as virtually all food crops come from rain-fed agriculture with irrigation covering only 2.5% of cultivated land (FAO, 2005). Rainfall has historically been highly erratic and is projected to become even more erratic as a result of climate change (IPCC, 2007, Schneider et al., 2008). Due to the high dependence of agriculture on rainfall, rainfall fluctuations directly translate into fluctuations of agricultural income.

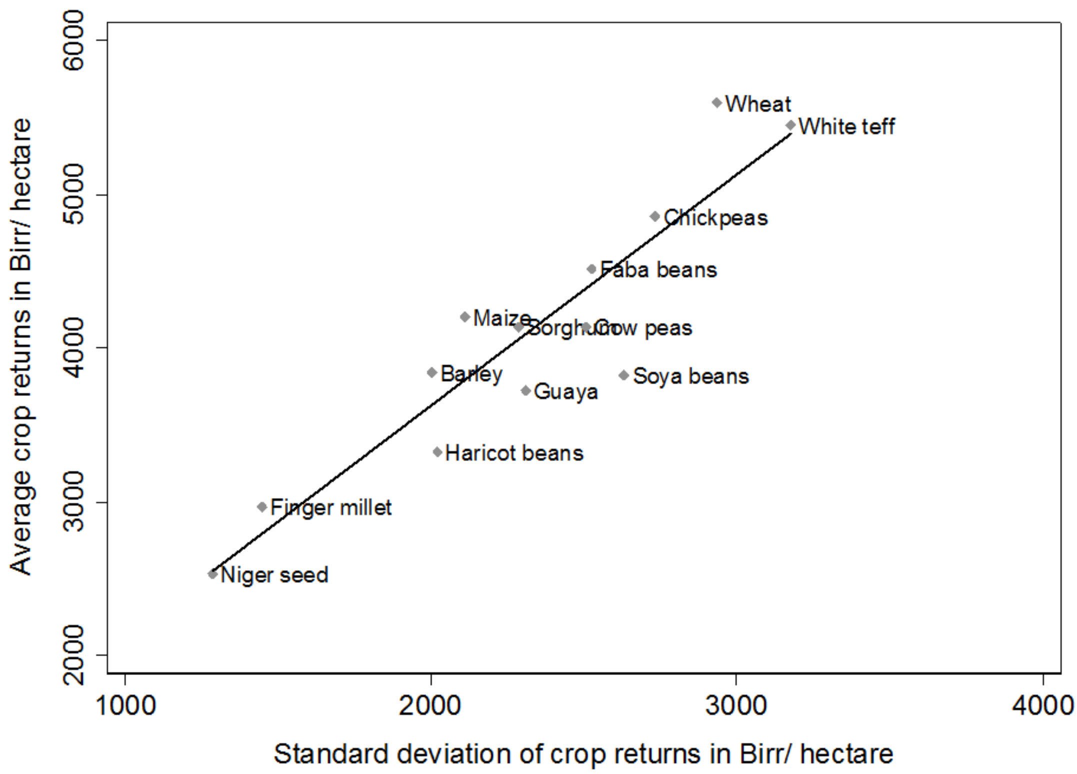
Third, farm household consumption is sensitive to fluctuations of agricultural income. As insurance against income losses is imperfect, farm households are not able to smooth their consumption levels over time. Thus, fluctuations of agricultural income reduce farm households' welfare. Empirical evidence from Ethiopia suggests that farm household consumption is particularly vulnerable to weather shocks. Having experienced at least one drought in the previous five years lowers per capita consumption by approximately 20% (Dercon et al., 2005). Rainfall shocks have long lasting and severe effects on consumption growth (Dercon, 2004) . In the same vein, consumption per adult equivalent is found to be significantly positively related with village level rainfall (Dercon and Krishnan, 2000).

Figure 5.1: Mean and standard deviation of returns to common crops (in Birr/ hectare; 16.67 Birr=1 USD) in Oromia region, 2003-2010; Own calculations based on data from the Ethiopian Central Statistical Agency (Agricultural Sample Survey and Producers' Prices of Agricultural Products Survey).

(a) All crops



(b) Enlargement of the marked area in the bottom left corner in Figure 1 (a)



The inability to protect household consumption from income fluctuations paired with the frequent arrival of covariate shocks requires Ethiopian farm households to carefully select crops regarding their drought resistance and tolerance to untimely rainfall. Given the risk-return tradeoff in crop cultivation, farm households may reduce the individual risk of crop failure by composing a low risk portfolio which, however, generates low average returns.

We base our analysis on a survey of Ethiopian small-holder farmers which we conducted in the East and West Shewa Zones of the Region of Oromia in spring 2011. The sample of farmers was randomly drawn from member lists of twelve agricultural cooperatives in the survey area. In total, we sampled 366 farmers from 23 different communities. The survey provides detailed information on crop cultivation decisions as well as a wide range of household and individual attributes. It also contains a set of questions that allow us to evaluate overconfidence in the sense of unrealistically positive self-evaluation and unrealistic optimism.

We determine whether a farmer evaluates himself unrealistically positive by comparing his self-assessed relative crop productivity with his actual relative crop productivity. To measure the self-assessed relative crop productivity, we asked each farmer to assess his average yields relative to the yields of other farmers from the same community on a three-point scale as worse (1), about the same (2), or better (3).

To measure the actual relative crop productivity, we evaluate whether a farmer's main crop productivity (in kg per hectare) falls into the $1st$, $2nd$, or $3rd$ crop productivity tercile in his community. The main crop is defined as the crop that occupies the largest cultivated area. The degree of unrealistically positive self-evaluation is then given by the difference between the self-assessed relative productivity (worse 1, about the same 2, or better than average 3) and the actual relative productivity ($1st$, $2nd$, or $3rd$ productivity tercile). The resulting measure ranges from -2 to 2. A value of zero implies that a farmer correctly assesses his relative crop productivity. Positive values correspond to overconfident farmers who think their yields per hectare are relatively higher than they actually are. Likewise, negative values correspond to underconfident farmers who think their yields per hectare are relatively lower than they actually are.

A fictive example helps to illustrate our measure of unrealistically positive self-evaluation. Consider a farmer who believes that his yields are on average higher than the yields of other farmers in his community (i.e. his self-assessed relative productivity takes a value of 3). He allocates the largest area of cultivated land to teff which makes teff his main crop. Compared to the overall distribution of teff yields in his community, however, his teff yields are relatively low and only fall into the first productivity tercile (i.e. his actual relative productivity takes a value of 1). We would therefore quantify his level of overconfidence in the sense of unrealistically positive self-evaluation with $3 - 1 = 2$.

Note that we base the measure of actual productivity on the main crop and not on the overall crop cultivation portfolio because the productivity of the overall portfolio depends on the allocation of land to different crops. As shown in the theoretical model above, the allocation of land to different crop is affected by overconfidence and hence no longer exogenous. In contrast, the productivity of a single crop, including the main crop, does not depend on the allocation of land and thus not on overconfidence.

We evaluate overconfidence in the sense of unrealistic optimism using an index of a farmer's optimism about not being hit by future covariate agricultural shocks. The index is based on a question that asked a farmer to state whether it is very likely (1), likely (2), unlikely (3), or very unlikely (4) that his household will be affected by each of the following three common shocks in the next twelve months: i) Large fall in sale prices of crops, ii) large rise in agricultural input prices and iii) very poor harvest due to drought/ shortage of rain. The index sums the stated levels of likeliness over the three shocks and is normalized to the [0, 1] interval. Higher values of the index correspond to more optimistic individuals. The index considers only covariate shocks as these would simultaneously affect all farmers in a given community. Hence, the true probability of the occurrence of these shocks should be identical for all farmers in the community. The selected shocks are very common in the study area. 75% of the households in the sample have experienced a large fall in sale prices of crops in the past five years, 90% a large rise in agricultural input prices and 86% a very poor harvest due to drought/ shortage of rain.

To capture the degree of risk taking in the crop cultivation decision, we measure the riskiness of the chosen crop cultivation portfolio. A widely accepted measure of portfolio riskiness is the variance or volality of portfolio returns. Hence, an ideal measure of the riskiness of a given portfolio would be the volatility of a farmer's returns to this portfolio over time.

Returns to a given portfolio in year i are defined as

$$Portfolio\, return_i = \sum_{j=1}^{n} area_j \; yield_{ij} \; price_{ij}$$

with $area_j$, the area in hectare allocated to $crop_j$ in the survey year 2011, $yield_{ij}$, the yield of crop j in year i in kg per hectare, and $price_{ij}$, the price per kg for crop j in year i in constant 2011 Birr (16.67 Birr=1 USD).

However, this measure is hard if not impossible to observe. Even if longitudinal data of crop portfolio returns were available for individual farmers, one would still not be able to measure the volatility of returns to a specific portfolio. This is because farmers typically change the composition of their portfolio and do not exhibit constant productivity over time (e.g. because of idiosyncratic productivity shocks such as serious illness).

We therefore use historical data on average yields and prices of different crops in the study region to evaluate the riskiness of a crop cultivation portfolio that a farmer chose in 2011. The underlying logic is that a larger volatility of average returns to a portfolio should correspond to a larger volatility of individual returns. In particular, we first calculate the average returns to a given portfolio for different years using average yearly yields and prices for the period 2003-2010 that are specific to the Region of Oromia. We then calculate the standard deviation of portfolio returns over time and divide it by the area of the cultivated land. To ease interpretation, we finally normalize this measure such that it has a mean of zero and a standard deviation of one. The resulting measure of risk taking captures the per hectare volatility of average returns to a given portfolio.

Information on average yields comes from the Ethiopian Agricultural Sample Survey. It is an annual survey conducted by Ethiopia's Central Statistical Agency to estimate crop cultivation areas and the volume of crop production in the main crop season. The survey covers a sample of more than 40 000 private farm households and is representative at the region level. Information on average prices comes from the Producers' Prices of Agricultural Products Survey, which is also conducted by Ethiopia's Central Statistical Agency. It provides monthly average producers' prices of agricultural products at the region level. Both yield and price data are available for the period 2003-2010. We can therefore compute the average returns to a given portfolio for this period which directly preceeds the survey year.

A theoretically important determinant of risk taking is a farmer's risk attitude. We therefore conducted a monetarily incentivized choice game to study risk behavior under high monetary incentives. Our experimental elicitation of risk attitudes followed the standard procedure of Holt and Laury, 2002, with ten choices, each between a safe alternative A and a risky alternative B. In the first choice, the risky alternative B is very unattractive as the probability of winning the high amount (25 Birr $\approx$ 1.50 USD) is very low (0.1). The probability of winning the high amount increases from choice to choice by 0.1 until it amounts to one in the last choice, so that B dominates A in the last choice. The point at which a farmer switches from choosing the safe lottery A to choosing the risky lottery B allows inferring his coefficient of relative risk aversion. A higher number of safe choices corresponds to a higher degree of risk aversion (see Holt and Laury, 2002, for details). After a farmer had made all ten choices, he rolled a ten-sided die to randomly select one choice that was played out for real. The average payout was 17 Birr ($\approx$ 1 USD), almost equivalent to the daily wage of an unskilled farm worker at the time of the survey.

Being aware of the unfamiliarity of most farmers with the concept of probabilities, we paid particular attention to a simple and clear explanation of the choice game. In particular, we provided farmers with a visual presentation of the game using strings that contained ten beads with the color of a bead determining the payoff (see Figure D.1 in the appendix). A consistent response rate with only one switch from the safe to the risky option of 89% of the sample makes us confident that the majority of respondents fully understood the rules of the game. Table 5.1 provides the distribution of the elicited risk attitudes in our sample. Most farmers switched after at least five safe choices. They are hence relatively risk averse ($\beta < 1$), as assumed in our theoretical model above. Nevertheless, the average degree of risk aversion is relatively low in comparison to the initial study by Holt and Laury, 2002, and other studies in developing countries (e.g. Henrich and McElreath, 2002, Humphrey and Verschoor, 2004, Hardeweg et al., 2011, Yesuf and Bluffstone, 2009, Harrison et al., 2009).

Table 5.1: Elicitation of risk attitudes and distribution of elicited risk attitudes

		A		B		Number of			Range of coefficient of				
Choice	$\pi(x_1)$	x_1	x_2	x_1	x_2	safe choices	n	%	relative risk aversion				
1	0.1	13	11	25	1	0-1	25	7.67			β	$<$	2.05
2	0.2	13	11	25	1	2	26	7.98	2.05	$<$	β	$<$	1.55
3	0.3	13	11	25	1	3	35	10.74	1.55	$<$	β	$<$	1.18
4	0.4	13	11	25	1	4	42	12.88	1.18	$<$	β	$<$	0.86
5	0.5	13	11	25	1	5	81	24.85	0.86	$<$	β	$<$	0.57
6	0.6	13	11	25	1	6	60	18.4	0.57	$<$	β	$<$	0.28
7	0.7	13	11	25	1	7	36	11.04	0.28	$<$	β	$<$	-0.05
8	0.8	13	11	25	1	8	19	5.83	-0.05	$<$	β	$<$	-0.5
9	0.9	13	11	25	1	9-10	2	0.61	-0.5	$<$	β		
10	1	13	11	25	1		326	100					

Note: 16.67 Birr=1 USD.

5.4 Empirical analysis

Farmers are fairly inaccurate in estimating their relative crop productivity. In total, the sample is characterized by overconfidence. 46% of the farmers believe that their productivity is higher relative to other farmers in their community than it actually is. They thus view themselves unrealistically positive. 34% correctly estimate their productivity tercile. The remaining 20% underestimate their relative productivity.

Farmers differ considerably in their optimism about not being hit by future covariate agricultural shocks. The overall coefficient of variation of our optimism index is 0.39. However, it makes more sense to investigate the dispersion in the degree of optimism within communities, i.e. within a given covariate risk environment in which the objective probabilities of covariate shocks are identical. Even within communities the coefficient of variation of the index has an average value of 0.38, which points to the existence of unrealistic optimism among at least part of the farmers.

Using ordinary least squares, we regress risk taking as measured by the normalized standard deviation of portfolio returns per hectare on overconfidence:

$$Risk\ taking_k = \alpha + \beta\ overconfidence_k + X_k'\,\gamma + \epsilon_k$$

where $overconfidence_k$ is the degree of overconfidence of farmer k captured either by our measure of unrealistically positive self-evaluation or our measure of unrealistic optimism. X_k a vector of control variables and ϵ_k an error term. If overconfidence increases risk taking, we expect β to be positive.

Table 5.2 summarizes the results for unrealistically positive self-evaluation. Column 1 starts with a specification that controls for important dimensions of heterogeneity between farmers. The set of control variables comprises a farmer's age and his ability to write[5] and various proxies for household wealth including the size of a household's own land holdings and the ownership of a radio and mobile phone. We also include detailed measures of a household's demographic composition to proxy for on-farm labor supply. In addition, fixed effects at the cooperative level eliminate any type of local heterogeneity and ensure that we only compare farmers within the same local setting and risk environment. Unrealistically positive self-evaluation is strongly and positively associated with risk taking. The coefficient suggests that an increase in the overestimation of the actual main crop productivity tercile by one tercile corresponds to an increase in the volatility of portfolio returns per hectare by 0.09 standard deviations. Hence, holding everything else constant, changing a farmer's confidence bias from very underconfident (-2) to very overconfident (2) would increase the volatility of portfolio returns per hectare by 0.34 standard deviations.

We check the robustness of this result by gradually expanding the set of control

[5]We control for the ability to write instead of educational attainment as hardly any farmer in the sample has completed formal schooling.

variables. We first consider the possibility that our measures of overconfidence and risk taking may not reflect a farmer's actual traits and behavior, thus biasing the estimated relationship. Our measure of unrealistically positive self-evaluation may wrongly classify a farmer as overconfident if he had recently experienced an adverse idiosyncratic shock such as a serious illness. In that case, the observed relative productivity of a farmer in the current period may not be representative of his (unobserved) average relative productivity. As a farmer's self-assessed relative productivity refers to his average relative productivity, we would then overestimate his degree of overconfidence. For a given level of risk taking, this would lead to a downward bias in the coefficient of interest. We therefore add a dummy to the set of control variables that takes the value of one if a farmer experienced a severe idiosyncratic shock in the twelve months prior to the survey. We consider different types of shocks including serious illness or injury of a household member, death of a household member, fire, loss of land due to the reallocation of land as well as idiosyncratic agricultural shocks such as crop disease and pest. About 14% of the sampled farmers reported at least one of these shocks.

Likewise, our measure of risk taking may not be representative of the risk taking of an individual farmer. By using average returns to evaluate the riskiness of a crop cultivation portfolio, we may overestimate the degree of individual risk taking if a farmer takes appropriate measures to reduce his exposure to risks. In that case, the actual volatility of a farmer's portfolio may be lower than the assigned average volatility. For a given level of overconfidence, this would lead to an upward bias in the coefficient of interest. We therefore add a set of control variables that indicate the use of risk-reducing measures. In particular, we control for the share of cultivated land on which a farmer uses crop disease prevention, fertilizer and improved seeds.[6]

Column 2 shows that our previous result on the relationship between unrealistically positive self-evaluation and risk taking is robust to the inclusion of these additional control variables. Compared to Column 1, the coefficient of unrealistically positive self-evaluation is somewhat lower, but remains highly significant and positive.

In a last step, we also control for a farmer's risk attitude. Column 3 uses the experimentally elicited degree of risk aversion, Column 4 a self-assessment of risk aversion. The latter is based on a survey question that asked a farmer whether he would describe himself as somebody who generally tries to avoid risks or somebody who is willing to take risks. Both risk measures turn out to be insignificant and their inclusion does not affect the coefficient of interest.

Table 5.3 summarizes the results for unrealistic optimism. It follows the same structure as Table 5.2. As for the case of unrealistically positive self-evaluation, unrealistic optimism is strongly and positively associated with risk taking. The coefficient in Column 1 suggests that, holding everything else constant, changing a farmers perception

[6] In theory, a farmer may also use irrigation to reduce rainfall-related volatility in crop yields. In practice, however, irrigation is a very uncommon practice in the study area.

of the likelihood of not being hit by future covariate agricultural shocks from extremely pessimistic to extremely optimistic corresponds to an increase in the volatility of portfolio returns per hectare by 0.72 standard deviations.

Overall, we find clear support for our hypothesis that overconfidence in the sense of both unrealistically positive self-evaluation and unrealistic optimism increases risk taking.

Table 5.2: The relationship between risk taking in crop cultivation and overconfidence in terms of unrealistically positive self-evaluation

	Model 1	Model 2	Model 3	Model 4
Unrealistically positive self-evaluation	0.086***	0.069***	0.063***	0.070***
	(0.023)	(0.024)	(0.024)	(0.024)
Age	-0.001	-0.000	0.000	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Ability to write	-0.036	-0.012	-0.005	-0.013
	(0.050)	(0.050)	(0.052)	(0.050)
Size of own land holdings	-0.002	-0.002	0.006	-0.002
	(0.019)	(0.019)	(0.019)	(0.019)
Radio ownership	-0.044	-0.053	-0.042	-0.053
	(0.055)	(0.056)	(0.060)	(0.056)
Mobile phone ownership	0.045	0.013	0.058	0.014
	(0.048)	(0.048)	(0.051)	(0.048)
Nr hh members 0-9 years	0.001	0.001	-0.009	0.001
	(0.017)	(0.016)	(0.017)	(0.016)
Nr hh members 10-18 years	0.000	-0.003	0.000	-0.003
	(0.018)	(0.018)	(0.018)	(0.018)
Nr female hh members 19-54 years	-0.037	-0.011	-0.020	-0.010
	(0.032)	(0.031)	(0.032)	(0.031)
Nr male hh members 19-54 years	-0.056**	-0.055**	-0.052*	-0.055**
	(0.026)	(0.025)	(0.027)	(0.025)
Nr hh members 55 years or older	-0.047	-0.028	-0.041	-0.028
	(0.053)	(0.052)	(0.049)	(0.052)
Recent idiosyncratic shock		0.078	0.065	0.078
		(0.056)	(0.057)	(0.056)
Crop disease prevention		0.383***	0.357***	0.384***
		(0.095)	(0.098)	(0.096)
Improved seed usage		-0.002	0.015	-0.002
		(0.086)	(0.094)	(0.086)
Fertilizer usage		0.296**	0.322**	0.297**
		(0.135)	(0.138)	(0.135)
Risk aversion (experimentally elicited)			-0.001	
			(0.013)	
Risk aversion (self-assessed)				0.010
				(0.047)
Constant	-0.679***	-1.352***	-1.410***	-1.354***
	(0.177)	(0.222)	(0.235)	(0.223)
Locality fixed effects	Yes	Yes	Yes	Yes
Observations	341	341	303	341
R-squared	0.463	0.501	0.524	0.501

Results of OLS estimation. Dependent variable is the normalized standard deviation of average returns to the currently selected crop cultivation portfolio. ***/**/* denote significance at a 1/5/10 per cent level. Robust standard errors in parentheses.

Table 5.3: The relationship between risk taking in crop cultivation and overconfidence in terms of unrealistic optimism

	Model 1	Model 2	Model 3	Model 4
Unrealistic optimism	0.721*	0.650**	0.513*	0.673**
	(0.387)	(0.323)	(0.293)	(0.332)
Age	-0.002	0.002	0.000	0.002
	(0.007)	(0.007)	(0.007)	(0.007)
Ability to write	0.054	0.084	0.038	0.094
	(0.121)	(0.118)	(0.117)	(0.121)
Size of own land holdings	-0.024	-0.037	-0.029	-0.037
	(0.047)	(0.049)	(0.053)	(0.049)
Radio ownership	0.030	0.006	0.063	0.004
	(0.092)	(0.093)	(0.117)	(0.093)
Mobile phone ownership	0.069	0.021	0.060	0.008
	(0.142)	(0.135)	(0.151)	(0.135)
Nr hh members 0-9 years	0.005	0.015	0.005	0.016
	(0.035)	(0.035)	(0.036)	(0.035)
Nr hh members 10-18 years	0.008	-0.001	0.010	-0.003
	(0.040)	(0.038)	(0.041)	(0.038)
Nr female hh members 19-54 years	-0.034	0.033	0.011	0.025
	(0.039)	(0.041)	(0.043)	(0.041)
Nr male hh members 19-54 years	-0.008	-0.005	-0.001	-0.008
	(0.071)	(0.070)	(0.074)	(0.070)
Nr hh members 55 years or older	0.049	0.067	0.085	0.065
	(0.080)	(0.077)	(0.090)	(0.077)
Recent idiosyncratic shock		0.034	0.044	0.036
		(0.070)	(0.075)	(0.071)
Crop disease prevention		0.524***	0.564***	0.513***
		(0.150)	(0.172)	(0.147)
Improved seed usage		0.401	0.523	0.397
		(0.261)	(0.320)	(0.259)
Fertilizer usage		0.846***	0.840***	0.840***
		(0.313)	(0.318)	(0.311)
Risk aversion (experimentally elicited)			-0.057	
			(0.042)	
Risk aversion (self-assessed)				-0.119
				(0.091)
Constant	-0.910*	-2.402***	-2.126***	-2.394***
	(0.490)	(0.754)	(0.654)	(0.750)
Locality fixed effects	Yes	Yes	Yes	Yes
Observations	366	366	326	366
R-squared	0.182	0.247	0.272	0.250

Results of OLS estimation. Dependent variable is the normalized standard deviation of average returns to the currently selected crop cultivation portfolio. ***/**/* denote significance at a 1/5/10 per cent level. Robust standard errors in parentheses.

5.5 Conclusion

This paper studies the relationship between overconfidence and risk taking in an income generating process. In particular, we consider the impact of unrealistically positive self-evaluation and unrealistic optimism on risk taking of farmers who can allocate their cultivable land to different crops and thereby face a risk-return tradeoff.

In a first step, we theoretically show that overconfidence in the sense of both unrealistically positive self-evaluations and unrealistic optimism increases the share of cultivable land allocated to risky crops. The excessive riskiness of the chosen crop cultivation portfolio implies a higher than optimal volatility of returns, which in turn implies a welfare loss for the decision maker.

In a second step, we empirically test the theoretical prediction that overconfidence increases risk taking. Using a sample of small-holder farmers from rural Ethiopia, we find that farmers who overestimate their relative crop productivity or underestimate the probability of future shocks cultivate riskier crops.

Our findings suggest that observed fluctuations in agricultural income may not only be the result of adverse covariate shocks, but of psychological biases of individual farmers that distort their decision making. If consumption cannot be smoothed efficiently over time, as is typically the case in developing countries, overconfidence leads to a reduction of farm household's welfare.

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Chapter 6

Conclusion

This dissertation has explored human decision making in the following situations - whether or not to privately insure against the financial risk associated with longevity, which lottery to chose in an experimental choice siutation, how much effort to spend in preparing for a future exam and how much risk to take in earning income. A special focus has been put on the interface between economic and psychological approaches in explaining human decision making.

Chapter 2 has empirically investigated determinants of private pension insurance uptake of German households. Relevant factors suggested by theory and previous empirical work have been simultaneously assessed in a multivariate framework. Households have been found to take advantage of private information on expected lifetime in the pension insurance choice. Conditional on other relevant variables, households expecting to become old, are significantly more likely to take up supplementary private pension insurance. This can be interpreted as a sign of adverse selection in the German market for private pension insurance leading to rising insurance premia and low demand. However, the effect is quantitatively small which casts doubt on adverse selection as a satisfactory explanation of the low take up of private pension insurance. Additional explanations brought forward by the behavioral economics literature like the complexity of the product paired with limited financial literacy of the decision maker or aversion to losses from the annuity as a result of early death may shed more light on the annuity puzzle.

Chapter 3 has experimentally tested whether preferences are consistent with the independence axiom imposed in expected utility theory and the criteria of transparent and non-transparent stochastic dominance. In contrast to most related studies, the analysis has used a sample from a developing country. Violation rates of expected utility theory in the common ratio problem and rates of selecting stochastically dominated lotteries in this sample turned out to be comparable to those observed in samples from developed countries. Thus, poor subjects from developing countries seem to behave similarly to subjects from the western world in experimental risky choice situations.

Chapter 3 has furthermore analyzed which characteristics of the decision maker determine his consistency with these rationality criteria. The econometric results suggest that sociodemographic characteristics of the subjects only partly explain experimental choices. More educated subjects tend to violate expected utility theory more frequently, whereas we do not observe any relationship with violating the principle of stochastic dominance. No robust pattern regarding the influence of age, income or wealth of the respondent was identified. However, the analysis suggests that psychological traits of the decision maker like his trustfulness or optimism play an important role.

Chapter 4 has evaluated the costs of overconfidence during preparation for a future task. It has been theoretically shown that an overconfident individual invests less than optimal time in effort spending after having monitored his current preparation status. At the same time, overconfidence inflates performance expectations. As a consequence, performance and subjective well-being of the overconfident individual deteriorate. The theoretical predictions have been confirmed in an empirical application to a student learning process. The data clearly support a performance and happiness reducing effect of an overly optimistic assessment of one's existing knowledge prior to the final knowledge retrieval.

The finding of adverse effects of overconfidence is replicated in a completely different set-up in Chapter 5 of this thesis. Chapter 5 has focused on the relationship between overconfidence and risk taking behavior in an income generation process. In particular, the impact of overconfidence on risk taking through crop choice by farmers in a developing country has been considered. The phenomenon of overconfidence is demonstrated in a sample of poor small-holder farmers in Ethiopia. Farmers who evaluate their ability to generate crop yields unrealistically positive cultivate riskier crops. The excessive risk taking implies more pronounced fluctuations of returns. Part of the observed income volatility in developing agroeconomies thus seems to be caused by a biased assessment of the own abilities of decision makers. Again, overconfidence clearly causes a welfare loss to the decision maker and his dependents. They need to deploy costly ex post coping mechanisms to smooth consumption more frequently than if they made their production decision in an unbiased way.

Taken together, the findings support the hypothesis of overconfidence as a universal phenomenon. Moreover, the results suggest a substantial behavioral relevance of overconfidence in different decision making situations. Leaving possible motivational effects of overconfidence aside, it can be concluded that decision makers tend to be negatively affected by their biased decision making. Thus, measures such as regular performance feedback that allow people to see themselves in an unbiased mirror may help them to accomplish more efficient decision making and higher levels of well-being.

Appendix A

Appendix to Chapter 2

Derived Variable	Original Variables
PPI	f72m_4_imp
AVSLE	f06s_imp; f10s_imp; f90o1_imp; f90o2_imp; f91o1_imp; f91o2_imp; f91s_imp; f92o1_imp; f92o2_imp; f92s_imp
RISKAVERSE	f59a4_imp; f59a5_imp; f59a6_imp
IMPATIENT	f59c1_imp; f59c2_imp; f59c3_imp
FINLIT	f73eo6_imp; f73eo11_imp
CIVSERV	f24s1_imp; f24s2_imp; f54o1_imp; f54o2_imp
WORKER	f24s1_imp; f24s2_imp; f54o1_imp; f54o2_imp
SELFEMPL	f24s1_imp; f24s2_imp; f54o1_imp; f54o2_imp
FINWEALTH(EQ)	f73eo1_imp; f73eo2_imp; f73eo3_imp; f73eo5_imp; f73eo6_imp; f73eo11_imp; f78o3_imp; f78o4_imp; f78o5_imp; (f10s_imp)
OTHWEALTH(EQ)	f82o_imp; f68o_imp; f70o_imp; f84o_imp; f78o1_imp; f78o2_imp; (f10s_imp)
OTHINS(EQ)	f73eo9_imp; f73eo10_imp ; (f10s_imp)
AGE	f07o_imp; f10s_imp; f11o_imp; year
NRCHILD	f13o_imp
MARRIED	f09s_imp
PARTNER	f10s_imp
INCOME(EQ)	f54o1_imp; f54o2_imp; (f14o_imp; f18o_imp)
EAST	bula

Source: The German SAVE study 2005.

Table A.1: Derived variables and their underlying original variables

Variable	**Fraction of imputed observations**
f06s_ind	0.00
f07o_ind	0.02
f09s_ind	0.00
f10s_ind	0.00
f11o_ind	0.00
f13o_ind	0.01
f14o_ind	0.00
f18o_ind	0.01
f24s1_ind	0.03
f24s2_ind	0.02
f54o1_ind	0.15
f54o2_ind	0.13
f59a4_ind	0.04
f59a5_ind	0.04
f59a6_ind	0.04
f59c1_ind	0.01
f59c2_ind	0.02
f59c3_ind	0.03
f68o_ind	0.03
f70o_ind	0.03
f72m_4_ind	0.00
f73eo1_ind	0.14
f73eo2_ind	0.12
f73eo3_ind	0.15
f73eo5_ind	0.04
f73eo6_ind	0.09
f73eo9_ind	0.13
f73eo10_ind	0.08
f73eo11_ind	0.03
f78o1_ind	0.02
f78o2_ind	0.04
f78o3_ind	0.04
f78o4_ind	0.04
f78o5_ind	0.03
f82o_ind	0.02
f84o_ind	0.02
f90o1_ind	0.02
f90o2_ind	0.03
f91o1_ind	0.03
f91o2_ind	0.03
f91s_ind	0.02
f92o1_ind	0.03
f92o2_ind	0.03
f92s_ind	0.02
N	1320

Note: N is sample size (non-retired housholds).
Source: The German SAVE study 2005. Own calculations.

Table A.2: Fraction of imputed observations per underlying variable in estimation sample

	Without control variables		With control variables (1)		(2)		(3)		(4)		(5)		(6)	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
AVSLE	0.003**	0.013	0.003**	0.036	0.003**	0.043	0.003**	0.036	0.003**	0.044	0.003**	0.033	0.002*	0.097
RISKAVERSE	0.006	0.784	0.007	0.729			0.007	0.730			0.007	0.746	0.000	0.987
IMPATIENT	-0.080***	0.002	-0.041	0.165			-0.041	0.168			-0.040	0.179	-0.040	0.183
FINLIT			0.096***	0.000	0.098***	0.000	0.095***	0.000	0.098***	0.000	0.098***	0.000	0.088***	0.003
CIVSERV			0.179**	0.015	0.192***	0.010	0.181**	0.014	0.193***	0.009	0.182**	0.013	0.192**	0.011
WORKER			0.095***	0.001	0.100***	0.000	0.095***	0.001	0.100***	0.000	0.097***	0.000	0.109***	0.000
SELFEMPL			0.255***	0.000	0.265***	0.000	0.254***	0.000	0.263***	0.000	0.262***	0.000	0.266***	0.000
AGE			0.024***	0.001	0.024***	0.001	0.024***	0.001	0.024***	0.001	0.024***	0.001		
AGE2			-0.000***	0.001	-0.000***	0.001	-0.000***	0.001	-0.000***	0.000	-0.000***	0.000		
NRCHILD			-0.017*	0.054	-0.017**	0.048	-0.018**	0.041	-0.018**	0.036	-0.016*	0.067	-0.016*	0.055
PARTNER			0.023	0.309	0.022	0.320	0.019	0.394	0.019	0.410			0.035	0.124
MARRIED											0.015	0.501		
EAST			0.050**	0.029	0.049**	0.030	0.050**	0.028	0.050**	0.029	0.050**	0.029	0.049**	0.034
FINWEALTHEQ			0.001	0.432	0.001	0.423					0.001	0.433	0.005	0.145
FINWEALTHEQ2													0.000	0.960
FINWEALTH							0.000	0.475	0.001	0.467				
OTHWEALTHEQ			-0.000	0.527	-0.000	0.533					-0.000	0.531	0.001	0.306
OTHWEALTHEQ2													0.000	0.643
OTHWEALTH							-0.000	0.545	-0.000	0.551				
INCOMEEQ			0.000	0.315	0.000	0.299					0.000	0.302	0.000	0.866
INCOMEEQ2													0.000	0.695
INCOME							0.000	0.305	0.000	0.283				
OTHINSEQ			0.000	0.253	0.000	0.261					0.000	0.269	0.000	0.820
OTHINS							0.000	0.208	0.000	0.215				

Note: Dependent variable = PPI, sample size $N = 1320$ (non-retired households), * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: The German SAVE study 2005. Own calculations.

Table A.3: Marginal effects at the mean using Rubin's Rule for multiply imputed data for the model without control variables and six different specifications of the model with a vector of control variables

	Without control variables		With control variables											
			(1)		(2)		(3)		(4)		(5)		(6)	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
AVSLE	0.003**	0.034	0.003*	0.065	0.003*	0.067	0.003*	0.066	0.003*	0.069	0.003*	0.060	0.002	0.135
RISKAVERSE	-0.003	0.887	0.001	0.972			0.001	0.979			0.000	0.994	-0.005	0.819
IMPATIENT	-0.072***	0.007	-0.035	0.263			-0.035	0.265			-0.034	0.279	-0.035	0.264
FINLIT			0.095***	0.000	0.097***	0.000	0.094***	0.000	0.096***	0.000	0.097***	0.000	0.087***	0.001
CIVSERV			0.175**	0.016	0.183**	0.011	0.176**	0.016	0.184**	0.010	0.178**	0.015	0.184**	0.013
WORKER			0.094***	0.001	0.097***	0.001	0.094***	0.001	0.097***	0.001	0.095***	0.001	0.108***	0.000
SELFEMPL			0.233***	0.000	0.238***	0.000	0.232***	0.000	0.237***	0.000	0.240***	0.000	0.249***	0.000
AGE			0.023***	0.002	0.024***	0.002	0.024***	0.002	0.024***	0.002	0.024***	0.002		
AGE2			-0.000***	0.001	-0.000***	0.001	-0.000***	0.001	-0.000***	0.001	-0.000***	0.001		
NRCHILD			-0.018*	0.062	-0.019*	0.058	-0.019**	0.043	-0.020**	0.039	-0.017*	0.073	-0.017**	0.043
PARTNER			0.027	0.255	0.027	0.257	0.023	0.343	0.022	0.348			0.037	0.107
MARRIED											0.018	0.462		
EAST			0.051**	0.025	0.051**	0.025	0.051**	0.025	0.051**	0.025	0.051**	0.026	0.054**	0.016
FINWEALTHEQ			0.001	0.490	0.001	0.486					0.001	0.496	0.006	0.134
FINWEALTHEQ2													0.000	0.848
FINWEALTH							0.000	0.523	0.000	0.520				
OTHWEALTHEQ			-0.000	0.634	-0.000	0.640					-0.000	0.642	0.001	0.314
OTHWEALTHEQ2													0.000	0.617
OTHWEALTH							-0.000	0.637	-0.000	0.642				
INCOMEEQ			0.000	0.166	0.000	0.154					0.000	0.152	0.000	0.907
INCOMEEQ2													0.000	0.754
INCOME							0.000	0.166	0.000	0.153				
OTHINSEQ			0.000	0.285	0.000	0.280					0.000	0.304	0.000	0.868
OTHINS							0.000	0.245	0.000	0.241				

Note: Dependent variable = PPI, sample size $N = 1464$ (non-retired households including imputed dependent variables), * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: The German SAVE study 2005. Own calculations.

Table A.4: Average marginal effects using Rubin's Rule for multiply imputed data for the model without control variables and six different specifications of the model with a vector of control variables; sample includes observations with imputed dependent variable

Appendix B

Appendix to Chapter 3

Table B.1: Summary statistics for the regression sample

	Observations	Mean	Std. Dev.
Violation of EU (Allais)	365	0.403	0.491
Violation of transparent SD	366	0.071	0.257
Violation of non-transparent SD	365	0.553	0.498
No formal education	366	0.448	0.498
Some or completed primary education	366	0.459	0.499
More than primary education	366	0.093	0.291
Ability to write	366	0.596	0.491
Ability to calculate	366	0.874	0.332
Age 34-	366	0.126	0.332
Age 35-44	366	0.254	0.436
Age 45-54	366	0.251	0.434
Age 55-64	366	0.227	0.419
Age 65+	366	0.142	0.350
Trust	366	1.984	0.927
Optimism	366	0.429	0.166
Risk aversion	326	4.715	1.919
Household size	366	7.197	2.414
Size of own land holdings	366	3.432	2.369
Radio ownership	366	0.765	0.425
Mattress ownership	366	0.828	0.378
HH income 1st tercile	366	0.333	0.472
HH income 2nd tercile	366	0.333	0.472
HH income 3rd tercile	366	0.331	0.471

Table B.2: Variable description

Violation of EU (Allais)	Dummy=1 if subject chose AB* or BA* in the common ratio experiment
Violation of transparent SD	Dummy=1 if subject chose stochastically dominated lottery in experiment with transparent dominance relation
Violation of non-transparent SD	Dummy=1 if subject chose stochastically dominated lottery in experiment with non-transparent dominance relation
No formal education	Dummy=1 if subject has no formal education
Some or completed primary education	Dummy=1 if subject has some or completed primary education
More than primary education	Dummy=1 if subject has some, completed or more than secondary education
Ability to write	Dummy=1 if subject is able to write
Ability to calculate	Dummy=1 if subject answered math problem correctly
	"Suppose you want to buy bottles of softdrink in a shop. The shop sells a bottle of softdrink for 4 Birr.
	How many bottles can you buy if you have 20 Birr?"
Age 34-	Dummy=1 if subject is of age 34 years or younger
Age 35-44	Dummy=1 if subject is of age 35-44 years
Age 45-54	Dummy=1 if subject is of age 45-54 years
Age 55-64	Dummy=1 if subject is of age 55-64 years
Age 65+	Dummy=1 if subject is of age 65 years or older
Trust	Agreement with statement "In general, one can trust people."
	1=fully disagree, 2=somewhat disagree, 3=somewhat agree, 4=fully agree
Optimism	Sum of perceived unlikeliness of six future covariate agricultural shocks on scale 1 to 4, normalized to [0, 1]
Risk aversion	Degree of risk aversion as experimentally elicited by the round in which respondent switched to the risky option
Household size	Number of people in living in household
Size of own land holdings	Size of land in hectare owned by household
Radio ownership	Dummy=1 if household owns a radio
Mattress ownership	Dummy=1 if household owns a mattress
HH income 1st tercile	Dummy=1 if household income falls into first income tercile within sample
HH income 2nd tercile	Dummy=1 if household income falls into second income tercile within sample
HH income 3rd tercile	Dummy=1 if household income falls into third income tercile within sample

Appendix C

Appendix to Chapter 4

Model extension to more than one task

Let us consider a decision-maker who maximizes utility by allocating her time budget on effort spending for two different tasks, A and B, and leisure.
Utility in $t = \tilde{t}$ is given by

$$U_{\tilde{t}} = U_{\tilde{t}}(E_{\tilde{t}}[p_T^A], E_{\tilde{t}}[p_T^B], l_2) \tag{C.1}$$

with $\frac{\partial U_{\tilde{t}}}{\partial E_{\tilde{t}}[p_T^j]} > 0$, $\frac{\partial^2 U_{\tilde{t}}}{\partial (E_{\tilde{t}}[p_T^j])^2} < 0$ for $j = [A, B]$, $\frac{\partial U_{\tilde{t}}}{\partial l_2} > 0$, $\frac{\partial^2 U_{\tilde{t}}}{\partial (l_2)^2} < 0$.

For simplicity, we assume that the decision-maker is only biased with regard to the current knowledge relevant for task A, but unbiased with regard to task B. As before, the expected performance on task A is defined as the sum of the subjective current knowledge and the expected knowledge gain:

$$\begin{aligned} E_{\tilde{t}}[p_T^A] &= K_{\tilde{t}}^{A\,s}(e_1^A, a) + \Delta K_{\tilde{t}}^{A\,s}(K_{\tilde{t}}^{A\,s}, e_2^A, a) &\text{(C.2)} \\ &= (1+\gamma) K_{\tilde{t}}^{A}(e_1^A, a) + \Delta K_{\tilde{t}}^{A\,s}((1+\gamma) K_{\tilde{t}}^{A}, e_2^A, a) &\text{(C.3)} \end{aligned}$$

where $\gamma \geq -1$ and $\frac{\partial \Delta K_{\tilde{t}}^{A\,s}}{\partial e_2^A} > 0$, $\frac{\partial^2 \Delta K_{\tilde{t}}^{A\,s}}{\partial (e_2^A)^2} < 0$ and $\frac{\partial^2 \Delta K_{\tilde{t}}^{A\,s}}{\partial e_2^A \partial K_{\tilde{t}}^A} < 0$.
In case of task B, expected performance is defined as

$$E_{\tilde{t}}[p_T^B] = K_{\tilde{t}}^{B}(e_1^B, a) + \Delta K_{\tilde{t}}^{B\,s}(K_{\tilde{t}}^{B}, e_2^B, a) \tag{C.4}$$

where $\frac{\partial \Delta K_{\tilde{t}}^{B\,s}}{\partial e_2^B} > 0$, $\frac{\partial^2 \Delta K_{\tilde{t}}^{B\,s}}{\partial (e_2^B)^2} < 0$ and $\frac{\partial^2 \Delta K_{\tilde{t}}^{B\,s}}{\partial e_2^B \partial K_{\tilde{t}}^B} < 0$.
The sum of time spent on effort for tasks A and B and leisure needs to equal the total

time endowment:

$$e_2^A + e_2^B + l_2 = 1. \tag{C.5}$$

Maximizing (C.1) with respect to e_2^A, e_2^B and l_2 subject to (C.3), (C.4) and (C.5) yields the first-order conditions

$$\frac{\partial \mathcal{L}}{\partial e_2^A} = \frac{\partial U_{\tilde{t}}}{\partial E_{\tilde{t}}[p_T^A]} \frac{\partial E_{\tilde{t}}[p_T^A]}{\partial e_2^A} + \lambda = 0 \tag{C.6}$$

$$\frac{\partial \mathcal{L}}{\partial e_2^B} = \frac{\partial U_{\tilde{t}}}{\partial E_{\tilde{t}}[p_T^B]} \frac{\partial E_{\tilde{t}}[p_T^B]}{\partial e_2^B} + \lambda = 0 \tag{C.7}$$

$$\frac{\partial \mathcal{L}}{\partial l_2} = \frac{\partial U_{\tilde{t}}}{\partial l_2} + \lambda = 0 \tag{C.8}$$

which lead to the optimality conditions

$$\frac{\partial U_{\tilde{t}}}{\partial E_{\tilde{t}}[p_T^A]} \frac{\partial E_{\tilde{t}}[p_T^A]}{\partial e_2^A} = \frac{\partial U_{\tilde{t}}}{\partial E_{\tilde{t}}[p_T^B]} \frac{\partial E_{\tilde{t}}[p_T^B]}{\partial e_2^B} \tag{C.9}$$

$$\frac{\partial U_{\tilde{t}}}{\partial E_{\tilde{t}}[p_T^A]} \frac{\partial E_{\tilde{t}}[p_T^A]}{\partial e_2^A} = \frac{\partial U_{\tilde{t}}}{\partial l_2}. \tag{C.10}$$

According to (C.9), the expected marginal utilities of effort in the two tasks A and B are equalized. According to (C.10), the expected marginal utility of effort in task A equals the marginal utility of leisure in the optimum.

Analogous to the single task model, the expected marginal productivity of effort in task A is positive, but decreases with the bias γ. Thus, an increase in the bias γ reduces the expected marginal productivity of effort in task A, which corresponds to a decrease of the left-hand sides of (C.9) and (C.10). It therefore leads to less effort spent on task A, but more effort spent on task B and more leisure consumed in the optimal allocation.

This extended framework implies that underconfidence does not only come at the cost of inefficiently low consumption of leisure, but also inefficiently low effort spending on other tasks. Thus, underconfidence will be detrimental for overall achievement.

Tables

Table C.1: Variable description

Overconfidence	Estimated multiple choice test score/multiple choice test score - 1
MC score	Score in multiple choice test from 0 to 10
Estimated MC score	Estimated score in multiple choice test from 0 to 10
Percentage exam score	Score in exam/120 × 100
Estimated perc. exam score	Estimated score in exam/120 × 100
Grade	Exam grade from 0 (failed) to 10 (excellent)
Estimated grade	Estimated exam grade from 0 (failed) to 10 (excellent)
Satisfactory grade	Satisfactory exam grade from 0 (failed) to 10 (excellent)
High school grade	Average grade in high school from 0 (failed) to 10 (excellent)
Male	Dummy = 1 for male subjects
Economics student	Dummy = 1 for students majoring in economics
Happiness	Subjective well-being from 1 (very unhappy) to 10 (very happy)
Monetary incentives	Dummy = 1 for monetary incentives treatment

Table C.2: Summary statistics for the regression sample

	Observations	Mean	Std. Dev.
Overconfidence bias	108	0.21	0.57
MC score	108	5.95	1.91
Estimated MC score	108	6.39	1.37
Percentage exam score	108	60.84	14.40
Estimated percentage exam score	108	72.31	9.12
Grade	108	4.73	2.67
Estimated grade	107	5.61	1.68
Satisfactory grade	108	5.41	1.93
High school grade	108	5.96	1.73
Male	108	0.60	0.49
Economics student	108	0.36	0.48
Happiness	90	6.03	2.74
Monetary incentives	108	0.45	0.50

Table C.3: Impact of monetary incentives on the confidence bias

	Dependent variable	
	|Bias|	Bias
Monetary incentives	-0.04	0.05
	(0.10)	(0.11)
High school grade	-0.03*	-0.03
	(0.02)	(0.02)
Economics student	0.15	0.29**
	(0.12)	(0.13)
Male	0.02	-0.07
	(0.09)	(0.10)
Constant	0.47***	0.3
	(0.15)	(0.18)
R squared	0.05	0.07
N	108	108

Results of OLS estimation. ***/**/* denote significance at a 1/5/10 per cent level. Robust standard errors in parentheses. As allocation to tutorial groups at the beginning of the semester was not random, a vector of control variables is included.

Appendix D

Appendix to Chapter 5

Figure D.1: Visual representation of the risk attitude elicitation game

Table D.1: Variable description

Riskiness of the crop cultivation portfolio	Normalized standard deviation of average returns to portfolio per hectare
Unrealistic positive self-evaluation	Self-assessed main crop productivity tercile–actual productivity tercile (the main crop is the crop that occupies the largest area)
Unrealistic optimism	Sum of perceived unlikeliness of three future covariate agricultural shocks on scale from 1 (very likely) to 4 (very unlikely) normalized to [0, 1]
Age	Age of household head
Ability to write	Dummy=1 if household head is able to write
Size of own land holdings	Size of land owned by household in hectare
Radio ownership	Dummy=1 if household owns a radio
Mobile phone ownership	Dummy=1 if household owns a mobile phone
Nr hh members 0-9 years	Number of children aged 0 to 9 years in household
Nr hh members 10-18 years	Number of youths aged 10 to 18 years in household
Nr female hh members 19-54 years	Number of female adults aged 19 to 54 years in household
Nr male hh members 19-54 years	Number of male adults aged 19 to 54 years in household
Nr hh members 55 years or older	Number of elderly aged 55 years or older in household
Recent idiosyncratic shock	Dummy=1 if household has experienced a severe idiosyncratic shock in the 12 months prior to the survey
Crop disease prevention	Share of cultivated land where households used disease prevention
Improved seed usage	Share of cultivated land where households used improved seeds
Fertilizer usage	Share of cultivated land where households used fertilizer
Risk aversion (experimentally elicited)	Degree of risk aversion as experimentally measured by the round in which household head switched to the risky option
Risk aversion (self-assessed)	Dummy=1 if household head describes himself as somebody who generally tries to avoid risks

Table D.2: Summary statistics for the regression sample

	Observations	Mean	Std. Dev.
Riskiness of the crop cultivation portfolio	366	2448.436	667.592
Unrealistic positive self-evaluation	341	0.352	1.020
Unrealistic optimism	366	0.429	0.166
Age	366	49.675	12.489
Ability to write	366	0.596	0.491
Size of own land holdings	366	3.432	2.369
Radio ownership	366	0.765	0.425
Mobile phone ownership	366	0.555	0.498
Nr hh members 0-9 years	366	1.710	1.323
Nr hh members 10-18 years	366	2.298	1.451
Nr female hh members 19-54 years	366	1.276	0.753
Nr male hh members 19-54 years	366	1.383	0.922
Nr hh members 55 years or older	366	0.527	0.665
Recent idiosyncratic shock	366	0.137	0.344
Crop disease prevention	366	0.717	0.294
Improved seed usage	366	0.233	0.317
Fertilizer usage	366	0.781	0.220
Risk aversion (experimentally elicited)	326	4.715	1.919
Risk aversion (self-assessed)	366	0.260	0.439

Eidesstattliche Erklärung

Ich erkläre hiermit an Eides statt, dass ich meine Doktorarbeit "Subjective Self-Assessment and Decision Making under Uncertainty" selbständig und ohne fremde Hilfe angefertigt habe und dass ich alle von anderen Autoren wörtlich übernommenen Stellen, wie auch die sich an die Gedanken anderer Autoren eng anlehnenden Ausführungen meiner Arbeit, besonders gekennzeichnet und die Quellen nach den mir angegebenen Richtlinien zitiert habe.

Kiel, den 25.03.2013